Essays in Political Economics and Political Communication

A thesis presented for the degree of
Doctor of Philosophy by

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Declaration

I declare that this thesis has not been submitted as an exercise for a degree at this or any other university and it is entirely my own work.

Chapter 3 of this thesis is co-authored with Diego Zambiasi. Chapter 4 of this thesis is coauthored with Nicola Mastrorocco and Arianna Ornaghi.

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Francesco Barilari

Non-Technical Summary

This dissertation consists of three essays on political economics with a particular focus on the effect of political communication. First, it studies how politicians way of speaking reacts in the aftermath of a salient shock on a divisive topic and which consequences this change may have on the policy making. Second, it studies how the political campaigning influence the behavior of law enforcement officers. Finally, it studies how politicians respond in their way of communication to a change in the traditional media content.

The first essay (Chapter 2) studies political polarization on multiple dimensions and its implications for the democratic process. A measure of political polarization is constructed based on the 1999-2016 congressional speeches of United States Representatives. By leveraging politically divisive events, such as mass shootings, as exogenous shocks, it implements a dynamic difference-in-differences design exploiting variation across different places and time. The paper documents that mass shootings significantly increase polarization on the gun rights topic. Furthermore, it explores how the distance between Democrats and Republicans increases over a range of different topics, revealing the contagious nature of polarization. The essay investigates different possible mechanisms behind these results, particularly focusing on the behavior of politicians following salient events, and presents a theoretical framework that motivates the findings. Finally, the essay explores how the increase in polarization impacts the democratic process, finding that in the days following a mass shooting event, the probability of passing a new law in the House of Representatives decreases. These effects have long-lasting implications as bills voted after such divisive events are also less likely to pass in the future. This research contributes to the understanding of the dynamics of polarization and its consequences for democratic governance.

The second essay (Chapter 3) shows that political campaigning can influence the behavior of law enforcement officers. The essays follows monthly arrests for 1383 police agencies in 40 American States from January 1984 to December 1990. During these years the Presidents of the United States developed a strong rhetoric against drug abuse. The main target of the presidential rhetoric was crack cocaine, a drug that the media associated with Blacks. The paper implements both a difference-in-differences and a reduced-form-Bartik-type approach to test if exposure to the presidential rhetoric affected the behavior of law enforcement officers. This essays generates a novel measure of the intensity of the presidential rhetoric against drug abuse by running a topic model analysis of all the public papers of Presidents Reagan and Bush. The paper finds that arrests for drug possession of Blacks increased more in counties more exposed to the presidential rhetoric against drug abuse, while there is no effect for Whites. The mechanisms of the paper rely on the possibility that politically competitive counties were more exposed to the presidential rhetoric against drug abuse. Indeed, local newspapers in these counties discussed the "War on Drugs" more often than non politically competitive places. Moreover, individuals in counties more exposed to the presidential rhetoric held more negative attitudes towards Blacks, perceiving them as receiving more than they deserved and needing to try harder to succeed, suggesting that the presidential rhetoric affected individual attitudes. The essay contains a series of robustness checks, including a no impact on arrests for other drugs or crimes.

The third essay (Chapter 4) examines how changes in traditional media content affect online communication. Specifically, it investigates the impact of the Sinclair Broadcast Group's acquisitions of local TV stations on the Twitter activity. It first studies how the same change in the content reported in the traditional media happen on the social media of the TV stations as well. Moreover, the essay shows how there is a change in the social media content of the United States Representatives. By analyzing the content of politicians' tweets, the study reveals that after Sinclair enters a media market, politicians are less likely to mention the local municipalities within their congressional district on Twitter. This effect is completely driven by those tweets referring to local events or local politics and policies. Furthermore, politicians online communication tends to lean more conservative. Overall, this research sheds light on how media consolidation can shape local news coverage and influence the online discourse of elected officials.

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Dedication

To Arnalda, Carlo, Enrico and Ileana

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Chapter 1

General introduction

This dissertation consists of three essays that delve into the field of political economics. It specifically focuses on how politicians' behavior reacts to various, and very different, shocks that the world presents to them with a particular focus on their communication. In the realm of politics, the power of language cannot be understated. Among the myriad of works exploring the intricacies of political language, George Orwell's seminal essay, "Politics and the English Language", stands as a timeless and thought-provoking piece. Orwell's work critically examines the degradation of language in political discourse and its profound consequences on the clarity of thought and the erosion of democratic principles and may be summarized in the famous sentence: *"Political language is designed to make lies sound truthful and murder respectable, and to give an appearance of solidity to pure wind"*.

Drawing inspiration from Orwell's insights, this dissertation wants to illuminate the immense power wielded by political language and its far-reaching implications for citizens, policy-making, and society as a whole. The aim of this research is to explore the dynamic relationship between political discourse and various aspects of policy-making, democratic processes, law enforcement behavior, and social media. By analyzing the political communication in these domains, this study aims to contribute to a deeper understanding of the intricate interplay between politics, economics, and communication. The findings of these essays hold implications for both scholars and policymakers. Understanding these dynamics is key for developing effective strategies for policy implementation, enhancing democratic processes, and promoting informed public discourse.

Embracing an empirical approach, each chapter employs a rigorous econometric framework to demonstrate how politicians' communication strategies can have direct or indirect consequences on our societies. To advance the academic understanding of the topics under examination and foster policy relevance, this thesis integrates novel text analysis and machine learning techniques into the causal estimation frameworks. Throughout the entirety of this dissertation, the United States of America serves as the primary case study, providing key takeaways into the dynamics of political language within a specific context. This is because, the United States offers a compelling setting for studying political economy due to its global influence, diverse economic systems, rich data and policy relevance. The rest of the thesis is divided as follows.

The first essay (Chapter 2) investigates how politicians react to a shock on a divisive topic in their way of communication. More precisely, by focusing on congressional speeches, it shows how a salient shock on a divisive topic may trigger a widespread reaction also on other political topics not directly related to the previous one, increasing polarization. This result highlights how political polarization on a divisive topic is contagious, trickling down onto other political issues. After establishing this, the essay turns to the consequences of increased polarization in the political system.

Political polarization has been the subject of numerous studies and discussions, highlighting its significance in understanding the dynamics of contemporary politics and social dynamics. Indeed, this phenomenon has significant implications for public opinion, electoral behavior and policy-making processes (McCarty, Poole and Rosenthal, 2016; Levendusky, 2013). The existing literature has predominantly focused on examining political polarization as a standalone concept, using a singular metric and studying its long-term effects. However, this approach poses certain limitations, as it fails to account for the multifaceted nature of political issues. Furthermore, it is crucial to recognize that at any given moment, a society may exhibit varying levels of polarization across different topics. Hence, it becomes imperative to adopt a more comprehensive measure of polarization, particularly when analyzing the short-term dynamics. This paper sheds some lights on these problems by leveraging politically divisive events, such as mass shootings, as exogenous shocks to political polarization. It implements a dynamic difference-in-differences design exploiting variation across space and time. The paper documents that mass shootings significantly increase polarization on the topic of gun rights. Furthermore, it explores how the distance between Democrats and Republicans increases over a range of different topics, revealing on the one hand the contagious nature of polarization, and on the other hand confirming the multidimensional concept of this phenomenon. After examining the potential mechanisms underlying these findings, the essay delves into the impact of increasing polarization on the democratic process and the composition of Congress. The analysis reveals that in the aftermath of a mass shooting event, there is a decreased probability of passing new legislation in the House of Representatives. This finding aligns with existing literature on the relationship between polarization and congressional gridlock (Binder, 2014; Lindqvist and Östling, 2010)). Furthermore, the essay uncovers a novel insight: it demonstrates that these effects have enduring implications, as bills voted upon following such divisive events are also less likely to pass in the future. This research contributes to our understanding of polarization dynamics and their consequences for democratic governance not just on the short term, but also on the medium-long term.

The second essay (Chapter 3) investigates how political campaigning influences law enforcement officers' behavior. Political campaigning can have profound effects on individuals' behavior, as seen in the recent Capitol Hill attack, where harsh political communication ignited violence. The social sciences have extensively studied the connection between political campaigning and violence against minorities, demonstrating that social media activity (Müller and Schwarz, 2020), political rallies (Grosjean, Masera and Yousaf, 2022), and election outcomes (Romarri, 2020) can trigger violent behavior.

This essay focuses specifically on the second mandate of President Ronald Reagan's administration in the United States. It examines the Reagan administration's "War on Drugs" campaign, which targeted crack cocaine abuse, to determine if the presidential rhetoric against drug abuse affected law enforcement behavior and whether the impact disproportionately affected minorities. This study focuses on two pivotal moments in the United States War on Drugs: the enactment of the 1986 and 1988 Anti Drug Abuse Acts (ADAA). Despite these laws primarily targeting crimes with interstate components, such as drug trafficking, they are considered examples of "dog whistle" politics (Haney-López, 2014). These acts are seen as conveying a call to action against stereotypical crack cocaine abusers and shifting law enforcement agents' efforts by "going public" (Kernell, 2006). By employing a difference-in-differences methodology and a Bartik-type reduced form, the study analyzes geographic variation in exposure to the presidential rhetoric against drug abuse and time variation in its intensity. The analysis distinguishes between arrests for possession of crack cocaine among Black and White individuals. The research reveals that exposure to the presidential rhetoric against drug abuse significantly increased arrests for possession of crack cocaine among Black individuals but had no statistically significant effect on arrests for White individuals. The study shows no significant impact on arrests for other drugs or crimes associated with crack cocaine use, such as marijuana consumption, prostitution, robbery, driving under the influence, or murder. To assess the intensity of presidential rhetoric against drug abuse, a novel measurement approach is employed, utilizing a collection of 11,171 public papers released by Presidents Reagan and Bush between 1984 and 1990. By applying a Latent Dirichlet Allocation (LDA) topic model, the study identifies the most frequently discussed topics, enabling the quantification of rhetoric intensity. Additionally, the research investigates the influence of political competition and media on law enforcement behavior, examining local newspaper articles and outcomes of Republican mayoral elections. The findings indicate that the presidential rhetoric against drug abuse played a substantial role in intensifying law enforcement efforts related to crack cocaine possession, particularly among Black individuals. These results contribute to the existing literature on racial discrimination within law enforcement and the criminal justice system. They underscore the systemic discrimination and unequal treatment experienced by minority communities due to heightened law enforcement activities triggered by presidential rhetoric. Understanding the impact of political campaigning on law enforcement behavior is crucial for addressing the racial biases inherent in the criminal justice system. By identifying the link between political campaigning and law enforcement actions, policymakers can work toward reforming policing practices and reducing disparities in arrests and convictions for drug offenses.

The third essay (Chapter 4) studies how changes in traditional media content affect online communication. An extensive body of research highlights the influence of media content on individuals' political preferences and voting decisions (DellaVigna and Kaplan, 2007), and on the role of media in shaping politicians' behavior (Snyder Jr and Strömberg, 2010; Ferraz and Finan, 2008). On the other hand, little is known about the potential interconnections between the traditional and social media.

This essay addresses this gap by examining alterations in traditional media content resulting from the acquisition of local TV stations by the broadcast group Sinclair. First, it shows how the same change in content on the traditional media propagates on the social media of the TV stations. Then, it focuses on a group of United States Members of the House of Representatives, studying whether changes in traditional media content influence the topics they discuss on their Twitter feeds. The essay employs a differences-in-differences design, leveraging the staggered timing of Sinclair's acquisitions. Firstly, it demonstrates the impact of Sinclair's acquisitions on both TV station online content and politicians' discourse. To assess the latter, the essay analyzes the Twitter feeds of U.S. Representatives, using a novel measure to proxy for the attention given to local issues. Additionally, it employs the recent "A la carté" embedding regression technique (Rodriguez, Spirling and Stewart, 2021) to measure conservative slant. The results of this study unveil a significant trend: after Sinclair enters a media market, representatives from congressional districts within that market tend to alter their online discourse. Specifically, they show a tendency to reduce their attention to local matters while increasing the expression of conservative viewpoints. These findings contribute to our understanding of how media not only affects election outcomes (Gentzkow, Shapiro and Sinkinson, 2011) and voter behavior (DellaVigna and Kaplan, 2007), but also impacts the way politicians communicate.

Chapter 5 briefly summaries the results of the thesis, further expands on the implications of the results, the methodology and the data employed and provides an outline of possible future venues of research. By analyzing how language, rhetoric, and media content react to different shocks and their possible consequences on policy-making, democratic processes, law enforcement behavior, and public discourse, this dissertation informs policymakers and scholars about the power of political communication. The findings highlight the need for thoughtful and responsible political communication to promote inclusive governance, address systemic biases, and ensure a well-informed and engaged citizenry.

Table 1.0.1: Summary of the research studies

	Shooting Political Polarization	**Political Campaigning, and Racial Discrimination in Arrests for Drug**	**Traditional Media, Social Media and Local Politics in the United States**
Authors	Francesco Barilari	Francesco Barilari, Diego Zambiasi	Francesco Barilari, Nicola Mastrorocco, Arianna Ornaghi
Own-contribution	Data collection, analysis, writing.	I jointly took care of the data collection; analysis, in particular on measuring rhetoric and text analysis applied in the paper. I suggested and implemented different robustness checks and mechanisms. I jointly drafted the manuscript.	I collected all the US politicians and TV stations Twitter account and their tweets. I constructed the outcome variables using text analysis techniques. I helped in defining the treatment and the design of the empirical strategy. I led the data analysis and drafted the manuscript.

Chapter 2

Shooting Political Polarization

2.1 Introduction

The ideological controversy between political factions is a defining feature of democratic societies, where multiple perspectives and voices coexist. However, recent decades have witnessed a considerable and excessive rise in political conflict, with both citizens and policymakers becoming increasingly divided along ideological and partisan lines. The literature defines this phenomenon as political polarization (DiMaggio, Evans and Bryson, 1996). This fact is particularly clear in a two-parties democratic system such as the United States of America (US). As a matter of fact, in the US, the ideological distance between Republicans and Democrats has sharply increased (Gentzkow, Shapiro and Taddy, 2019). This evidence stems from congressional voting records (McCarty, 2016), candidate survey responses (Conley, 2019; Moskowitz, Rogowski and Snyder, 2018), congressional speech scores (Gentzkow, Shapiro and Taddy, 2019), and campaign donation measures (Bonica, 2014). Understanding the origins and impact of political polarization is crucial. It affects policymaking and the likelihood of passing new policies (Epstein and Graham, 2007). Additionally, it influences people's decisions, leading to social divisions (Baldassarri and Gelman, 2008; McCarty, 2016).

Existing literature has primarily focused on political polarization as a singular concept, measured using a single metric. However, this approach overlooks the fact that there are multiple political issues and that polarization can vary across these topics at any given moment. The interaction and contagion between polarizations on different topics remain unclear. However, studying this is essential for gaining a comprehensive understanding of societal divisions and developing effective strategies to mitigate the negative impacts of polarization on communities and democracies. This paper aims to fill this gap by exploring the research question: Is political polarization contagious? It investigates whether polarization on a specific issue can trigger a widespread polarization effect across other unrelated political topics. Furthermore, it reveals that this increase in polarization has both short and long-term consequences on the velocity and quality of policy-making.

More precisely, I focus on the topic of gun rights, one of the most divisive topics of the US political landscape (Conley, 2019). By analyzing the impact of mass shooting events (MSEs), which serve as salient shocks on the divisive topic of guns, the study overcomes endogeneity concerns and demonstrates that polarization not only increases on the focal issue but also spills over to other political topics.

To study this I construct a novel and more flexible measure of polarization by analyzing the 531501 congressional speeches of the US Representatives generated from 1999 to 2016[1]. Drawing upon various text analysis techniques (Ash and Hansen, 2023), I build my measure which I define rhetorical polarization. This measure highlights the stark contrast in the way individuals from different political parties communicate about the same issue.

Exploiting mass shooting events as a quasi-random natural experiment, the paper implements a dynamic differences-in-difference approach. It compares level of polarization among politicians from states directly affected by the shooting and not before and after the occurrence.

The paper reveals that the days after a shooting incident, polarization intensifies not only on gun-related issues but also on topics that are not directly associated with firearms, such as social policy, war and defense, environment, and justice. The effect is particularly pronounced among Democratic and Republican Representatives from states directly impacted by the shooting.This finding underscores the contagious nature of political polarization, with its influence extending beyond a divisive topic to impact other political issues. The spread of political polarization across various issues can be linked to psychological theories such as confirmation bias and cognitive dissonance (Nickerson, 1998).

Notably, concerning gun rights, the analysis demonstrates a significant increase of 21% compared to the mean outcome, emphasizing the magnitude of polarization specifically on this issue. This result serves two important purposes. Firstly, it acts as a crucial sanity check by aligning with expectations, validating the hypothesis that polarization would intensify regarding gun rights[2]. Secondly, it serves as a valuable validation of the proxy used to measure polarization, affirming the accuracy and reliability of the chosen approach.

However, the extent of impact varies across topics. Certain areas, particularly those

[1] How individuals interact in group discussions can provide essential insights into the position of the politicians and party in a particular topic at a specific time (Karakowsky, McBey and Miller, 2004). Moreover, who decides to intervene and when a politician speaks are mechanisms for collective decision-making (Blumenau, 2019)

[2] MSEs are likely to attract significant media attention and trigger strong emotional responses (Benton, Hancock, Coppersmith, Ayers and Dredze, 2016), thereby amplifying existing political divisions.

related to the economy, remain unaffected by these divisive shocks. To delve deeper, I employ a more specific topic model (Structural Topic Model, STM), to dissect the macro areas[3] into more precise micro topics. The results reveal that the increase in polarization aligns with the specific macro political issues, with some micro topics being more affected than others.

To gain deeper insights, I conduct heterogeneity analyses to uncover the drivers behind these outcomes. One would expect that the salience of these events may play a crucial role in influencing the magnitude of polarization. The severity, the location and the timing of a MSE may change the reaction and the attention a politician and the public opinion direct toward it. I hence examine three different sources of heterogeneity: the number of fatalities, whether the shooting occurred in a school, and whether it took place around an electoral period. This analysis reveals that the increase in the polarization is primarily propelled by shootings with higher numbers of fatalities, whereas incidents within school or university campuses do not yield statistically significant effects. Additionally, the timing of these events does not seem to matter. The analysis indicates no statistically significant difference in the impact during the final six months of a Congressional period, coinciding with electoral campaigns.

Employing an event study approach, I demonstrate that the effect remains present for several weeks following the occurrence of the event. Furthermore, there is no statistical difference in polarization among the treated and non-treated states in the weeks leading up to the mass shooting, providing reasonable evidence for the assumption of parallel trends.

To strengthen the support for my findings and to elucidate the underlying mechanisms, I develop a novel theoretical model which explains the contagious nature of polarization and the varying impact on different topics. This theoretical framework is grounded in the concepts of cultural and economic conflict (Bonomi, Gennaioli and Tabellini, 2021) as well as intra-party competition (Canen, Kendall and Trebbi, 2021). The model help me in explaining why some topics are responding, while others not.

I study whether my results may be related to some characteristics of the speakers. Indeed, if, after a salient event, more extreme politicians from both parties are more inclined to speak out compared to their moderate counterparts, this could explain the increase in political polarization. Their heightened involvement may be driving polarization across different topics. I provide suggestive evidence to establish that the observed results are not influenced by the identity of the speakers. Specifically, I find no statistically significant difference in the probability of a more extreme or moderate

[3] social policy, environment, war and defense, economy, and justice

candidate delivering a speech after a divisive event[4].

Finally, we know from the literature that when dealing with political polarization we should distinguish between ideological and affective polarization (Iyengar, Lelkes, Levendusky, Malhotra and Westwood, 2019). I demonstrate that a significant portion of the observed increase in polarization can be attributed to the latter. Affective polarization is defined by the literature as the gap between individuals' positive feelings toward their own political party and negative feelings toward the opposing party (Druckman, Klar, Krupnikov, Levendusky and Ryan, 2021). To measure affective polarization, I employ a proxy by analyzing the Twitter feeds of each US Representative and constructing a sentiment score. The analysis reveals that after a divisive event, when a treated politician discusses their opponents (candidates from the same state but from another party), they employ more negative terms compared to their previous statements and compared to other members of the House of Representatives.

After establishing the role of salient and divisive events in driving rhetorical polarization and exploring the mechanisms behind this phenomenon, I delve into the consequences of increased polarization within the political system and its impact on policy-making. Building upon previous research (Krehbiel, 1996; Romer and Rosenthal, 1978), one would naturally anticipate that an increase in political polarization would lead to a heightened inability to pass legislation, resulting in congressional gridlock. While existing literature has explored this phenomenon, there remains a significant knowledge gap concerning the potential impacts of polarization on congressional gridlock in the medium to long term. Additionally, it remains uncertain whether all policies are equally affected by this polarization.

This study aims to address these gaps. Specifically, I find that the probability of passing new policies decreases following a divisive event, such as a mass shooting, confirming the already existing relationship between polarization and congressional gridlock. Notably, this effect is particularly pronounced for moderate policies. However, extreme policies, whether conservative or liberal, appear to be less affected or even unaffected by this polarization. Furthermore, by tracking the trajectory of these policies over time, I observe that they face even lower probabilities of passing in the future compared to other policies that were not passed during less polarized periods.

These discoveries offer some insights into the medium to long-term effects of polarization on policy-making and introduces a new understanding of the heterogeneous ways in which policies are more impacted by political polarization.

To further explore the long-term implications, I investigate how these divisive events may impact the future composition of the House of Representatives. In the congres-

[4]Measured using the DW-nominate suggested by Poole and Rosenthal (1985)

sional districts affected by such shocks, I find a higher probability of electing an extreme candidate in the future compared to non-treated districts. However, I do not observe a statistical difference in the likelihood of electing a Republican or Democrat representative. This observation may suggest that the change occurs primarily on the supply side of the political environment, indicating an impact on the type of candidates running for office rather than a shift in the preferences of voters between the two parties.

This paper relates to three different strands of the literature. First, it contributes to a growing literature that argues that, in addition to historical and cultural motivations, political polarization also reacts to unrelated and specific events (Demszky, Garg, Voigt, Zou, Gentzkow, Shapiro and Jurafsky, 2019). The findings in this paper also suggest that salient and local events shift the polarization among politicians (Burden, 2001). To the best of my knowledge, this is the first paper showing how contagious polarization is across topics. Indeed, a salient shock on a divisive topic triggers polarization not just on the specific topic but also on other issues not directly related to the former one.

This paper also relates to the new literature on text as data (Gentzkow, Shapiro and Taddy, 2019). Using text analysis techniques, I compute polarization in different topics identified using a topic model (Martin and McCrain, 2019). I follow a dictionary-based sentiment analysis (Fei, Liu, Hsu, Castellanos and Ghosh, 2012; Mohammad and Turney, 2013) to compute a measure of polarization through the sentiment of the words used by the individual. This paper contributes to this literature by introducing the multidimensional concept of rhetorical polarization. Indeed, previous works on this field consider it as a general phenomenon. In contrast, with this work, I show that political polarization can have different dimensions and movements based on the topic.

This work also contributes to the political economy literature on public attention, policymaking, and law. Empirical research on policymaking emphasizes that factors beyond social welfare influence policy (Luca, Malhotra and Poliquin, 2020; Bardhan and Mookherjee, 2010; Makowsky and Stratmann, 2009). As I show in the last part of the paper, the days immediately after an MSE register a reduction in the Congress' legislative activity, suggesting a decrease in the probability of voting and introducing a new law.

The paper proceeds as follows. In the next two sections, I give an overview of the causes and consequences of political polarization and which data I use. Section 4 explains how I construct my outcome variable for measuring political polarization through text analysis. Section 5 outlines the estimation strategy, and Section 6 describes the main results. Section 7 presents the mechanisms behind my results. Finally, Section 8 shows how polarization impacts legislative activity and the future composition of the House of Representatives, and Section 9 concludes.

2.2 Institutional Context

This study aims to demonstrate how a divisive topic shock can heighten polarization and how this polarization spreads to other political topics. In this section, I explain how the literature define political polarizationa and how I refer to it in this paper. Moreover, I describe the divisive topic I analyze and the main shock to it used in the paper.

2.2.1 Political Polarization in the US

Definition. Political polarization is a widespread and significant phenomenon in almost all the Western democratic systems today. Its baseline definition is the ideological distance among parties. In a two party design democratic system, the political polarization incorporates all frictions of its binary ideologies and partisan status. Scholars have defined political polarization in various ways, using different settings and measurement techniques. DiMaggio, Evans and Bryson (1996) define the political polarization as both a state and a process, where party opinions on issues can be opposed due to ideological motivations or historical factors, while also evolving over time. In the United States, the polarization between Republicans and Democrats has today sharply increased reaching its highest level in history (Gentzkow, Shapiro and Taddy, 2019).

When talking about political polarization it is also important to remember that it can be divided into two levels: elite (politicians) and mass (citizens) (Fiorina and Abrams, 2008) and how these two characters interact with each other (Baldassarri and Gelman, 2008). From the literature, the term “political elites” defines members of Parliament, and all the other influential players in the political process. While “mass polarization” refers to the polarization of the electorate or general public (McCarty, Poole and Rosenthal, 2016).

In this paper, I define the rhetorical polarization as a compelling proxy for measuring political polarization. This measure highlights the stark contrast in the way individuals from different political parties communicate about the same issue. When two individuals, each representing opposing parties, address a specific topic, their language, tone, and arguments tend to diverge significantly. This divergence may signify a deep-rooted ideological divide, ultimately shaping the political landscape. The strength of rhetorical polarization lies in its ability to capture the essence of the larger ideological conflict in a more disaggregated way, showcasing, at least in part, how partisanship and biases can influence the way individuals perceive and discuss issues. However, one of its weaknesses is that it mainly focuses on the surface level of communication and may not fully reflect the underlying reasons for political polarization. Nonetheless, examining rhetorical polarization remains valuable in shedding light on the divisive nature of contemporary politics and its implications for democratic discourse.

Causes. Various factors contribute to the rise of political polarization in the US.

Congressional primaries play a role as candidates adopt extreme positions to appeal to voters (Burden, 2001). Changes in US political geography, such as the dominance of Republicans in the South, contribute to increased conservatism (Mann and Ornstein, 2006; Jacobson, 2000; Fleisher and Bond, 2004; Stonecash, 2018). Another possible motivation has to be found in a change in the socio-demographic characteristics of the country. For example, the increase in inequality parallels that of political polarization. The inequality and economic shocks facilitate the election of extreme candidates and polarization (McCarty, Poole and Rosenthal, 2016; Autor, Dorn, Hanson and Majlesi, 2020). Fiorina, Abrams and Pope (2005) also propose religion as a possible element in favor of the political polarization. Another driver for the current rise in the political polarization has to be found in the media (Levendusky, 2013; Mutz, 2006). Furthermore, the recent increase in partisanship could be also motivated by a new way of doing politics: to dislike and distrust those from the other party is currently becoming the normal way of expressing a political position (i.e. affective polarization, Iyengar et al. (2019)).

Consequences. Political polarization has wide-ranging effects on society, politics, and the democratic process, with both positive and negative consequences (Layman, Carsey and Horowitz, 2006).

One of the possible positive consequence of the political polarization is the clarity of candidates. Polarized politicians offer divergent messages and use a language that citizens can easily understand. There is substantial evidence that public participation in American politics has increased with amplified polarization (Abramowitz and Stone, 2006). The polarization may help voters to elaborate on the substance of candidates (Layman, Carsey and Horowitz, 2006).

The political polarization phenomenon, on the other hand, has different negative consequences impacting both the political process and society. These studies show that Congress enacted more significant legislation pieces when it was less polarized. Political polarization may impact the quality of policies voted and passed Binder (2000); Epstein and Graham (2007); Canen, Kendall and Trebbi (2020). The data also shows how the partisan polarization is adversely affecting the federal judiciary's independence (Binder, 2005). Moreover, the polarization may also undermine the leadership of a country in foreign policy, damaging its image in the world (Beinart, 2008). Besides, polarized environments fundamentally change how citizens make decisions (Druckman, Peterson and Slothuus, 2013). The mentioned situation can influence individuals' civil behavior, creating a more and more divided society.

2.2.2 Guns Right as a divisive topic and MSE as a shock

The main objective of this paper is to study how a salient event affecting a divisive topic, influences not only polarization on that particular topic but spread polarization also to those not related to it. I am considering as a divisive topic the issue of gun rights. Guns Right is one of the most divisive topics today in the US (Conley, 2019). This fact is true both for politicians and citizens. The Democratic position on this topic is completely opposed to the Republican one. Gun rights supporters favor fewer government gun regulations, while those favoring gun control advocate for more (Jouet, 2019). Gun rights support is a function of non-social practical concerns as well as a reinforcement of political, social identity (Kohn, 2004). Support for gun control, however, has not been a marker for individual identity core values (Parker, 2017).

This paper uses mass shooting events as shocks on this divisive topic. Previous works which exploited mass shootings as a plausible exogenous variation (Duwe, 2007; Krouse and Richardson, 2015) distinguished public mass shootings from private ones. I categorize shootings following the definition given by the FBI: *"Mass Shooting is an event that involved three victims (excluding shooter) in any public or private place. The event is not directly related to gangs, drugs, or organized crime"*. Following this definition, also terrorist attack or gang and drug related shootings are not defined as a mass shooting event. The literature previously used these shocks to study their economic, social and political impact on society with a particular focus on the voters (Yousaf, 2021). Mass shooting events have significant damaging effects on the victims and their families. Furthermore, such tragedies hit the communities where they occur, and they don't influence only those directly affected. Indeed, these events hurt community well-being and emotional health outcomes that capture community satisfaction, sense of safety, and levels of stress and worry (Soni, Tekin et al., 2020; Dursun, 2019). We know that mass shootings evoke significant policy responses, so study their effect on politicians ideology or position is a relevant research question in particular for its policy-making consequences. Indeed, these episodes may also affect the implementation of new gun policies at the state level (Luca, Malhotra and Poliquin, 2020), but we still don't know if there any effects in the policy making at the national level. Demszky et al. (2019) studies how the mass shooting events impact the individuals' views on the topic by studying individual tweets after 21 shootings.

The literature in this area has considered how to extract information on gun violence from the news (Pavlick, Ji, Pan and Callison-Burch, 2016) as well as quantify public opinion on Twitter (Benton et al., 2016) and across the web (Ayers, Althouse, Leas, Alcorn and Dredze, 2016). So, we should expect to see a reaction from politicians after such events, however is still not clear if this reaction may spread on other political topics and having also medium-long term effects on the policy-making and congressional composition.

2.3 Data

In this paper, I combine data from different sources which I describe in more detail in this section.

Political Speeches. I categorize politicians' positions on different topics by analyzing the speeches through text analysis techniques. From the "United States Congressional Record", and from Gentzkow, Kelly and Taddy (2019), I collected all the political speeches (House of Representatives) from 1999 to 2016 (from the 106th Congress to the 114th one). The speeches follow a congressional meeting daily edition, and they present characteristics about the speaker: name, surname, party, state, district. I removed all non-Democrats or non-Republicans representatives' speeches, the Speakers' interventions, the President and Vice-President speeches. Finally, I exclude the Extensions of Remarks, which contains speeches, tributes, and other extraneous words that were not uttered during open proceedings of the full Senate or the full House of Representatives (this procedure was already suggested in Gentzkow, Kelly and Taddy (2019)). For each remaining speech I apply different normalization procedure in the text. From these speeches I extract the main topics and sentiment and I compute my measure of rhetorical polarization (I explain in more details these steps and how I measure it in the next section).

Mass Shooting Events. The paper exploits mass shooting events as a quasi-natural experiment to study the impact of these facts on rhetorical political polarization. There are different definitions for mass shooting event. In this paper, I am considering the one of "active shooter" given by the FBI (which is also my main source). The agreed-upon definition of an active shooter by U.S. government agencies—including the White House, U.S. Department of Justice/FBI, U.S. Department of Education, and U.S. Department of Homeland Security/Federal Emergency Management Agency—is "an individual actively engaged in killing or attempting to kill people in a confined and populated area." Implicit in this definition is that the subject's criminal actions involve the use of firearms. Following this definition, it is possible to count 203 mass shooting events in the US territory from 1999 to 2016. Not all the states were treated, while some states were treated more than once.

I have collected data on mass shootings since 1999 from two different sources. The first one is the FBI supplementary homicide reports (SHR), which I complemented (Luca, Malhotra and Poliquin, 2020) with data on mass shootings collected by the Mass Shootings in America (MSA) project at Stanford University (Stanford, 2017). With these two sources I am able to collect information on the shooter and on the victims. Moreover, they collect the precise location and time of the shooting and the number of victims and injuries of the event. Finally, from these sources, I also have an idea of the reason for the gun violence. For each shooting, I determine the location and date of the event, the characteristics of the shooter, the number of fatalities and injuries, and the possible motivation. The majority of these shootings is classified as ”unknown” by the FBI

Other works also divide shootings between public or private depending on the locations where such events occurred (Duwe, 2007; Krouse and Richardson, 2015). I use this information to run a heterogeneity test for understanding if shooting happening in a school generates a different reaction or not. Finally, in these sources are not reported all those shootings related to criminal organizations (gangs, terrorist attacks, drug cartels).

Twitter. Using the Twitter Developers Research Track I collect tweets of US politicians for the period 2009-2016.

I start from 2009 and not before because Twitter started to be widely used among US politicians in 2009. In the 111th Congress (2009-2010) almost 40% of the Congresspeople had an active Twitter account, while from 2011 this percentage increased to 60% (112th Congress) and became 85% in the 113th Congress. I use the tweets to study how politicians react to a divisive event on social media. More precisely, I use this data to proxy for affective polarization (Iyengar et al., 2019). By using a regular expression, I then identify the tweets of each representative talking about another representative from the same state, but from the other party. I then compute the sentiment score of each tweet. I the mechanism section I explain in a more comprehensive way this measure and how I use it.

Roll Call Votes and Politicians ideological score. To study if and how policy implementation is affected by an MSE, I collected from Voteview (Lewis, Poole, Rosenthal, Boche, Rudkin and Sonnet, 2019) the roll call votes data. In particular, this data includes the result and ideological parameters of every poll taken in the selected congressional period (in my case, from 106th to 114th; 1999-2016). Ideological positions are calculated using the DW-NOMINATE (Dynamic Weighted NOMINA ONE Three-step Estimation developed in Poole and Rosenthal (1985)). In this database, it is possible to have information on the topic of the policy as well (Issue, Clausen and Peltzman codes). I supplemented this information by collecting from the Library of Congress data on bill characteristics, sponsorship and co-sponsorship and the text of the bill.

Finally, from the Congressional Bills Project I have further information on the topic of the policy (Adler and Wilkerson, 2015). From Voteview (Lewis et al., 2019) I also have information about the ideological position of each US member of Congress over years. There, we can find two estimates of a legislator's ideology: NOMINATE and Nokken-Poole. NOMINATE estimates assume that members occupy a static ideological position across the course of their career. Nokken-Poole estimates assume that each congress is completely separate for the purposes of estimating a member's ideology. Moreover, this measure is time variant. In the last part of the paper I use this measure for understanding if after a salient event the probability to elect an extreme candidate increases.

Control Variables. This paper exploits different control variables depending on the specification.This data includes basic biographical information of each US congressperson (state, district, party, name). I also include demographic characteristics at the state level as part of these controls [5]. The main source for these variables is Census and the National Center for Education Statistics. I also add a dummy variable for capturing the period before a Democratic or Republican Primary Election.

2.4 Measuring Political Polarization

To find a measure of political polarization which varies across times and topics is not so straightforward for many reasons. In this work, I identify a new measure of polarization based on the sentiment of the words used by a politician to express a position about a precise argument. I call this measure rhetorical polarization. This measure quantify how differently members of the Congress, from different parties, talk about the same topic. Although the rhetorical polarization may not capture completely the change in the ideological position, it helps to show that politicians of different parties change their way of communicate after a shock. This measure is just a proxy for the real level of polarization on a topic in a precise moment, however it is still relevant for the purpose of this study and informative.

This paper uses as main outcome variable the rhetorical polarization between Republican and Democratic speakers on different topics. To extract a quantitative measure

[5] Population at the Congressional District or at the State level, employment rate at the state level, education.

from the political speeches, I apply a sentiment analysis using a semi-supervised machine learning approach (or dictionary-based methods Fei et al. (2012)[6]).

To define what the speaker is talking about, I use a topic model technique. I identify the most important discussed topics in my dataset running two different topic models: a Structural Topic Model (STM - Roberts, Stewart and Tingley (2019)) to identify more specific topics (micro topics) and the more common Latent Dirichlet Allocation (LDA) model (Blei, Ng and Jordan, 2003) to identify the most general topics (macro topics[7]). In appendix I explain in more details the pre-processing applied to the specches and these procedures.

To determine the guns topic, I also follow a different approach as a robustness check. I recognize whether a speech is about guns using a pattern-based sequence-classification method. This method defines if a speech is about guns if it contains bigrams that are much more likely to appear in an external gun-related library (Mastrorocco and Ornaghi, 2020). The gun related training library is composed of articles from the Metropolitan Desk of the New York Times the day of or the day after each shooting with the tags gun violence, mass shooting events, or gun rights. I focus on bigrams because they convey more information than single words within a particular topic. Figure 2.B.1 shows a word-cloud with the 50 bigrams that have the highest weight for the gun rights topic. The bigrams I identify to be about guns are quite general and make intuitive sense. In addition, they do not display an ideologically driven view of the gun, which lowers the concern of measurement error.

Having assigned the topic and applied the sentiment analysis approach, I compute polarization as the absolute distance between the Democratic and the Republican sentiment score[8].

$$Sentiment\ Score^{J}_{i,s,t} = [\sum_{j=1}^{n} Positive\ Words^{J}_{s,t} - \sum_{j=1}^{n} Negative\ Words^{J}_{s,t}] \times topic_{i,s,t} \tag{2.1}$$

$$Polarization_{i,s,t} = abs[Sentiment\ Score^{D}_{i,s,t} - Sentiment\ Score^{R}_{i,s,t}] \tag{2.2}$$

$Sentiment\ Score^{J}_{i,s,t}$ is the sentiment score of party J computed as the total positive words minus the negative ones spoken by speakers of the party J state s on topic i

[6] Figure 2.B.4 shows a word cloud as an example of negative and positive words in my corpus of speeches.

[7] Figure 2.B.5 shows the 15 most spoken words for each topic.

[8] To make the interpretation of the results easier, I standardize the variables when I present the results for the different topic together

at the congressional meeting day t. I normalize the $Sentiment\ Score^{J}_{i,s,t}$ by the total number of positive and negative words spoken by speakers of the party J state s on topic i at the congressional meeting day t. $Polarization_{i,s,t}$ is Polarization in topic i, in state s, at congressional meeting day t, computed as the absolute difference between Democratic position in topic i, in state s at day t and the Republican one.

2.4.1 Possible concerns about the measure

This measure is a proxy for rhetorical polarization. If on the one hand is a simple and useful method for the purpose of my paper, on the other hand may raise some concerns about its validity. There are three possible concerns: construction, measurement error and definition.

The measure is constructed by assuming that the sentiment of a speaker is uniformally distributed across topics.

Another possible concerns relies on the error present in the measure. The measurement error in this case is likely to be as good as random (both in positive and negative words); it is affecting the Democrat and Republican speakers in the same way and my identification strategy (difference in differences design) should solve any problem of measurement error.

About the definition, this measure is impacting the language used to talk about a topic not the content. It is no a direct ideological measure, but it presents a change in the way of talking about the same arguments. In the results session, I will show that this measure may be helpful to show how two politicians from the same geographical area, but from different party, are distant in the their way of talking about the same topic using the A la Carte embedding method (Khodak, Saunshi, Liang, Ma, Stewart and Arora, 2018).

2.5 Empirical Strategy

Identification Strategy. The main objective of this paper is to study how a salient event affecting a divisive topic, influences not only polarization on that particular topic but spread polarization also to those not related to it. I am considering as a divisive topic the issue of gun rights. The significant challenge for answering my research question is finding a shock to the Gun Rights topic exogenous to my measure of polarization. I address the issue by exploiting mass shooting events (MSE).

The empirical strategy of this work is a difference-in-differences design that compares the rhetorical polarization of politicians in places with and without a mass shooting event, before and after the occurrence. Using panel data at the state-day of the congressional meeting level, I compared polarization in different periods among states directly and not directly affected by the shooting, both before and after their occurrence. The main identifying assumptions for my empirical strategy are that there are no pre-determined characteristics which may motivate a place to have an MSE compared to another, and that these events are exogenous with respect to my outcome variable. Figure 2.5.1 plots the mass shooting events from 1999 to 2016. This figure show that, unfortunately, it is not possible to predict when and where the next mass shooting will occur. MSEs are staggered across places and time. For this reason, one could exploit these variations in place and time to study their effects on the polarization of politicians. Figure 2.B.2 and Figure 2.B.3 show the variation over time of the shooting and the motivations given by the FBI for the shooting. This evidence suggests that MSEs are exogenous to polarization and to politics in general. Moreover, in a more rigorous specification I introduce state by month fixed effects in order to take into consideration any seasonality trends at the state level that may bias my results.

Specification. To study the influence of a divisive shock on the polarization in different topics, I first use the following dynamic difference-in-differences specification:

$$Polarization_{i,s,t} = \beta_0 + \beta_1 MSE_{s,t-1} + \gamma \mathbf{X}_{s,t} + \mu_s + \lambda_t + \epsilon_{s,t} \tag{2.3}$$

where $Polarization_{i,s,t}$ is my measure for rhetorical polarization on topic i, in state s at the congressional meeting day t; $MSE_{s,t-1}$ is an indicator variable equal to one if in state s at day $t-1$ there has been a mass shooting event. $\mathbf{X}_{s,t}$ is a battery of baseline controls at state level interacted with congressional period fixed effects[9]. μ_s and λ_t are respectively state and day of the congressional meeting fixed effects. Standard errors are clustered at the state level; however, I discuss the robustness of the results to alternative assumptions about standard errors. Finally, I weight observations by the number of speakers, in order to make the estimates representative at the national level.

Since some states in my dataset experienced multiple treatment during the period taken into consideration, I exploit different time windows to allow the treatment to switch on and off. My preferred time window considers a state treated for the rest of the Congressional period once the treatment is assigned. I use shorter time windows

[9]Time invariant controls: demographic characteristics, unemployment rate, education level at the state level which I interact with Congress FEs. Time variant controls: a dummy variable indicating 30 days around the Republican or Democrat primary elections for each state . A variable identifying the number of extreme speakers present in a precise state in each congressional period (varying every two years) and a variable with the mean value of the DM-nominate of the state in a precise congressional period.

— 30 days, 1 semester and 1 year around the time of the shooting — to check that the results are stable and stronger immediately after such events as we would expect.

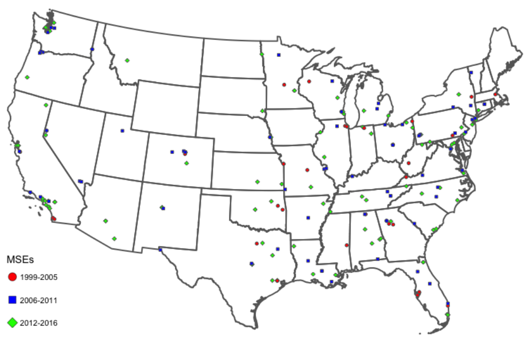
To verify if there are any pre-treatment characteristics which may select the treatment group, I exploit an event study specification. For the event study approach I transform my dataset at the month (or week) level to have more statistical power for the different topics and I follow this equation:

$$Polarization^{i}_{s,t} = \sum_{t=-q}^{-2} \gamma_\tau MSE_{s,\tau} + \sum_{\tau=0}^{m} \delta_\tau MSE_{s,\tau} + x_{s,t} + \mu_s + \lambda_t + \epsilon_{s,t} \tag{2.4}$$

where $Polarization_{i,s,t}$ is the rhetorical polarization on topic i in state s, at year-month t. I include q leads or anticipatory effects and m lags or post-treatment effects (excluding $t-1$ period). $x_{s,t}$ is a matrix including control variables[10]. μ_s and λ_t are state and year-month (or year-week) fixed effects. I omit the event time dummy at $t = -1$, implying that the event time coefficients measure the impact of MSE relative to the month (or week) just before the occurrence.

I then run different robustness checks following the recent literature on DID (Goodman-Bacon, Goldring and Nichols, 2019; De Chaisemartin and d'Haultfoeuille, 2020) to verify that my TWFE estimations are robust to the heterogeneity in time and unit in the treatment.

Figure 2.5.1: Variation across States and Years of mass shooting events



Notes: This figure shows the variation across states and years (6 years) of the mass shooting events present in my dataset.

[10] Time invariant controls: demographic characteristics, unemployment rate, education level at the state level, which I interact with Congress FEs. Time variant controls: a dummy variable indicating 30 days around the Republican or Democrat primary elections for each state. A variable identifying the number of extreme speakers present in a precise state in each congressional period (varying every two years) and a variable with the mean value of the DM-nominate of the state in a precise congressional period.

2.6 The effect of a salient shock on polarization

In this section I report the main results before discussing the heterogeneity and the robustness checks performed.

2.6.1 Divisive events and Polarization

Table 2.6.1 shows the results for the Equation 2.3 when i is the Guns Right topic. After an MSE, the distance in the way of speaking about gun rights between Republicans and Democrats from states directly affected by the shooting increases compared to the other states not affected by the shooting.

In particular, after a mass shooting, the treated states register an increase of almost 0.14 percentage point in the rhetorical polarization on guns compared to the control group. The results are statistically significant at 5% in my first specification which includes date of the speech and state fixed effects (column (1)). In column (2), I show my main specification including my battery of control time invariant variables interacted by year fixed effects. In column (3), I also include seasonality trends to account for periodic fluctuations in the outcome that may occur at regular intervals (in this case month level). Finally, in column (4) I run a more rigorous specification controlling for state by year fixed for taking into account any state policies change or shocks. The standard errors are clustered at the state level. In appendix, I report the same results as robustness by (i) clustering standard errors by date of the congressional meeting (Table 2.A.8), and by (ii) using two-way clustering by both state and congressional meeting day ((Table 2.A.9)). From these results we can understand that after a salient shock on a divisive topic, the rhetorical polarization on that topic rises sharply by between 21 and 25% with respect the mean outcome depending the specification used.

To study if and how rhetorical polarization is contagious is important to focus on how a salient shock impacts the other political topics both directly and not directly related to the divisive one. In Figure 2.6.1, I show that also the level in polarization on other topics is impacted by the MSE. Through the LDA topic model I identify the 5 most discussed topics: social policy, economy, environment, war and defense and justice and law[11].

Figure 2.6.1 shows how the polarization in all five topics is impacted positively, with the exception of the economy[12] topic which is not statistically impacted. The figure plots

[11]In Figure 2.B.5 I present the 10 most used words and their betas for each topic

[12]The justice and law topic is impacted at 10% is some of the specifications and robustness. See table Table 2.A.5.

Table 2.6.1: Polarization on Gun Rights Topic after MSE

	Polarization on Gun Rights			
	(1)	(2)	(3)	(4)
MSE	0.0014**	0.0014**	0.0015**	0.0016**
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Mean Outcome	0.0065	0.0065	0.0065	0.0065
Observations	20,997	20,997	20,932	20,932
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the guns' topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the guns topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by Congress period FE such as: log population, share male, share white, share black, share Hispanic, share unemployed and a time varying dummy variable representing the days aroung the Primary elections for each party at the state level. In column (3) I include seasonality trends. Finally, in column (4) I introduce state by year fixed effects. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

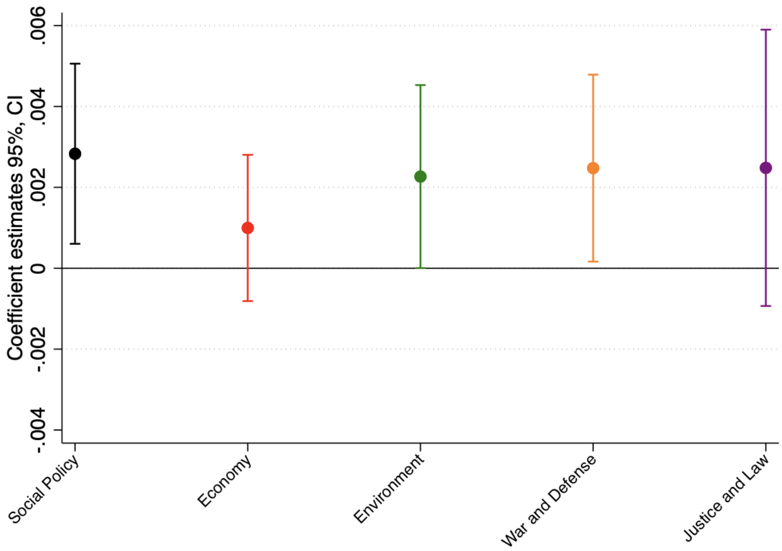
the coefficients of my baseline specification (column 2) including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects.

In appendix, I present the tables showing the estimates for each of the 5 topics using the different specifications used in the guns topic table (Table 2.A.1, Table 2.A.2, Table 2.A.3, Table 2.A.4, Table 2.A.5).

The rhetorical polarization is contagious, affecting positively and significantly different themes discussed in the House of Representatives. In particular, the polarization on the social policy topics, the environment, war and defense are more impacted after a shooting in all the studied specifications. The distance between democrats and republicans from the treated states is significantly higher in these topics than in the non-affected states at the 5% significance level, while the justice and law topic is as well positively impacted by at the 10% significant level. On the other hand, the rhetorical polarization on the economy topic does not seem to be affected after an MSE, the coefficients are never statistically significant, they are always close to zero and they become negative when introducing the state by year fixed effects. Thanks to the STM topic model, I am able to decompose the five Macro topics into the more specific political topics discussed in the congressional meetings (Micro topics).

In Figure 2.B.7 I report the estimates for the Micro topics divided by the five Macro

Figure 2.6.1: Polarization on the different Macro Topics and MSE



Notes: This figure shows the effect of mass shooting events on the 5 macro topics level of polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the 5 macro topics (social policy, economy, environment, war and defense, and justice and law), at time t. I show coefficients derive from my baseline specification including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period. Standard errors are clustered at state level.

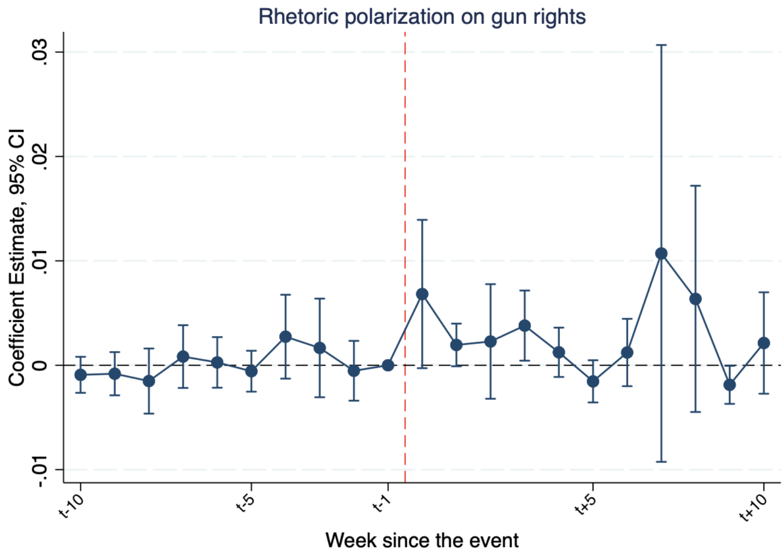
areas. The figure shows that the Micro topics of a Macro area move all in the same directions with different magnitude confirming the results presented in Figure 2.6.1. The estimates for these topics are noisier because not all congressional meetings present a discussion about so specific topics and because the weight assigned by the topic model is lower by construction for some of them because in general they are not highly discussed topics. More precisely, the rhetorical polarization on the so called "cultural identity" political topics increases, while the economic topic is not impacted. I will discuss the distinction between cultural and economic topics in the mechanism section, where I present a theoretical model based on this idea to support my finding and to show why some topics seem to be impacted more than others.

The political polarization may be contagious, as a matter of fact an increase in the polarization on a divisive topic may propagate into other political themes generating higher division than before in the way of talking. Moreover, the political polarization is a multidimensional concept, indeed, not all the levels of polarization are impacted in the same way.

2.6.2 Event Study Specification

To study how long this effect lasts and if it satisfies the parallel trends assumption, I exploit an event study specification following Equation 2.4.

Figure 2.6.2: Polarization on Gun Right Topic after MSE, Event Study Week level (TWFE)



Notes: This figure reports the event study estimates for the gun righst topic at the week level. The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. The omitted category is the week leading up to the shock. Standard errors are clustered at the state level.

Figure 2.6.2 shows how the parallel trends assumption is satisfied for the gun rights topic. Indeed, there is no statistical difference between level of rhetorical polarization on this topics in the treated and control groups in the weeks (and months from Figure 2.B.6) leading up to the mass shooting. This means that the republican and democrat speakers in these states don't use different terms in talking about this topic before the event compared to the others democrat and republican speakers of the House of Representatives. While, after the treatment, they start to change their way of communication compared to their colleagues going more distant than before. More interestingly, the effect lasts for at least one month after the shooting. The effect for the gun rights topic lasts for at least 5 weeks, and it then shades away.

In appendix, I report the event study plots for the five different Macro Topics at the month level. As in the previous case, there is no statistical difference between treated and control groups in the months leading up to the mass shooting. The effect in the different topics lasts differently. These graphs are less informative than the one on the gun rights topic, but they still present a clear pattern. First of all, not statistical difference between the treated and control group before the shock and then an immediate and short lasting jump after the event.

Recent work in the econometrics literature has highlighted that two-way fixed effects (TWFE) regressions (i.e., regressions that control for unit and time fixed effects) recover a weighted average of the average treatment effect in each group and time period

(De Chaisemartin and d'Haultfoeuille, 2020). This may be problematic because weights can be negative (Goodman-Bacon, 2021), which means that if treatment effects are heterogeneous, the TWFE estimates might be biased. I provide evidence that the impact of MSEs on the rhetorical polarization is robust to concerns related to heterogeneous treatment effects. In particular, I apply the machinery introduced by (Borusyak, Jaravel and Spiess, 2021) to the difference-in-differences specifications that underlie my DiD estimates.

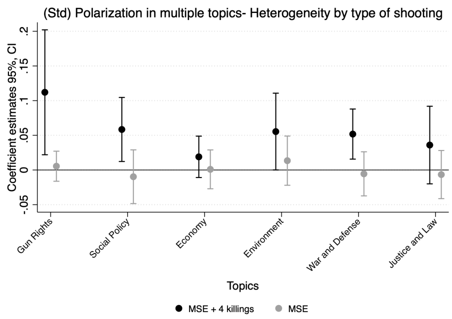
In Figure 2.B.9 I present event study results using the robust estimator proposed in their paper aggregating the outcome variables at the month level to gain more power. The outcome variable in each one corresponds to a level of polarization in the different topics (Gun rights, social policy, environment, war and defense, economy and justice and law). Reassuringly, the robust estimation shows treatment effects that are very similar to the baseline estimates from the difference-in-differences specifications. Given that the estimates that underlie my main effects are robust to allowing for treatment effects to be heterogeneous, I am confident in my DiD estimates as well. To further verify this, in Table 2.A.7 I report the DiD estimates using the Borusyak, Jaravel and Spiess (2021) estimator. Again, the TWFE estimates are robust to the different timing in treatment .

2.6.3 Does the saliency of the event matter?

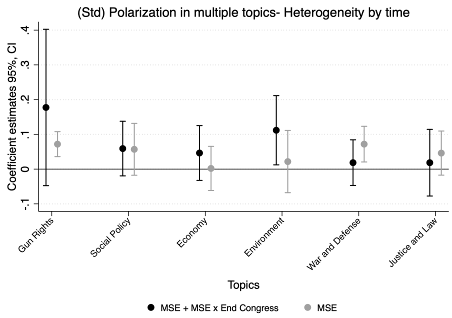
Are all the divisive events impacting polarization in the same way? I answer this question by studying different heterogeneity based on the salience of the event. I focus on two main different definitions of salience: number of fatalities of the MSE and the closeness of the MSE to the next congressional elections. The first heterogeneity should increase the importance and the public relevance of such an event. The second one should increase the attention that a politicians would invest on commenting such events. Indeed, if such an event happens close to the election, a politician may have more interest in talking about it to exploit the MSE as trigger for attracting more voters.

I defined two different dummy variables which I interact with my treatment variable: one for defining mass shooting events with more than 4 fatalities; and the second dummy is taking value 1 for those MSEs having occurred at least 6 months before the Congressional election (from May to October of each even year). These are characteristics that may generate more attention around the events, consequently attract more public attention, and/or, then, being more important for a politician. In Figure 2.6.3a, I report results for the heterogeneity based on the number of fatalities. In Figure 2.6.3b I present evidence for the heterogeneity based on the timing of the MSE. The outcome

Figure 2.6.3: Heterogeneity of the MSEs



(a) Heterogeneity by saliency - More than 4 Killings



(b) Heterogeneity by timing - Close election events

Notes: These figures report heterogeneity by saliecy. The outcome variables are respictively the standard level of rhetorical polarization on the gun rights, social policy, economy, environment, war and defense, and justice and law topics. In figure a, I interact the treatment with a dummy identifying thos mass shooting events with more than 5 victims; while in figure b, with a dummy identifying the last 6 months of a congressional period (May-October of each even year). The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects.

variable is the standardized level of rhetorical polarization for the gun rights topic and for the different macro topics I showed in the previous subsection. From the plots it is clear that the two definitions of salience matter in increasing the level of rhetorical polarization in different way. Indeed, an MSE involving more than 5 fatalities has a higher and statistically significant effect on polarization on the gun rights topic and on the other topics, compared to have involved less fatalities. The salience drives the majority of the findings. This evidence suggests that to activate the trigger-down effect of the political polarization the salience, in terms of how big is the event, matters. On the other hand, as concerning the timing the results are less clear. Indeed, we can't see a clear statistical difference between MSE happened close or far to election.

In appendix, I show a further heterogeneity for the salience by distinguishing between MSE school or not school related to understand if the location matters. For these particular MSEs the impact is not statistically difference with each other. In Figure 2.B.10 I report these results.

2.7 Possible Mechanisms

This section aims to explore the underlying mechanisms behind the main findings of this study. Specifically, it addresses several key questions: How are extreme or moderate speakers influencing polarization? Is affective polarization a contributing factor? And why does polarization vary across different topics?

2.7.1 Who is talking after a salient event?

In studying how the political polarization reacts after a salient shock on a divisive topic, it is relevant to understand who is talking after such an event. It is possible that after such a salient event, more extreme politicians from both parties are more inclined to speak out compared to their moderate counterparts. If this hypothesis holds true, it would justify the observed increase in polarization as a result of the heightened involvement of more extreme representatives, ultimately driving polarization across different topics.[13]. I verify this by constructing a dummy comparing extremist candidates with moderate ones as an outcome variable. Using the DW-Nominate score for each congressperson, I create a dummy variable that takes value 1 for very extreme candidates[14] and 0 otherwise.

Table 2.7.1 shows that after a salient topic, the probability that a more extremist candidate talks is not different from a moderate one. This is true in all the specifications studied. My results are not driven by the fact that after such divisive events the extremist Congresspeople speak more, or intervene, more than a normal day.

2.7.2 Affective Polarization

In the paper I report that after a divisive event, the level of polarization in different topics rises. However, from the literature we know that when talking about this phenomenon we should distinguish between ideological polarization and affective polarization. Affective polarization refers to the increasing negativity and animosity among individuals with differing political beliefs harbor. It is defined as *the tendency for partisans to dislike and distrust those from the other party* (Finkel, Bail, Cikara, Ditto, Iyengar, Klar, Mason, McGrath, Nyhan, Rand et al., 2020; Iyengar et al., 2019). In the extreme cases this may result in the dehumanization and demonization of opponents (Hopkins, 2018). This polarization can create a lack of empathy towards those with opposing viewpoints. It may also make it difficult for people to engage in civil discourse

[13] Assuming that, more extreme politicians use a more polarized language in expressing their views.

[14] I define more extreme candidates the one with $-1 <= DWscore <= -0.5$ or $0.5 <= DWscore <= 1$. Han and Brady (2007) uses similar bins for studying more conservative and more liberal candidates.

Table 2.7.1: Probability that an extreme representative talk after a salient shock

	Extreme candidate: DW-Nominate		
	(1)	(2)	(3)
MSE	-0.0310	-0.0040	-0.0276
	(0.0205)	(0.0592)	(0.0360)
Observations	505,056	505,056	505,056
Mean Outcome	0.2876	0.2876	0.2876
Date FE	Yes	Yes	Yes
State FE	Yes	Yes	No
State Time Trends	No	Yes	No
State x Year-month FE	No	No	Yes

Notes: This table shows the effect of a mass shooting events on the probability that an extreme candidate talk compare to a moderate. The outcome variable is a dummy equal one if the speaker talking in the day t is an extreme one (DW-nominate at the extreme) and 0 otherwise. I control for state characteristics: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (1) I include date, and state fixed effects. In column (2) I control for State-Time trends and in column (3) I include also state times Year-month FE. Standard errors are clustered at state level. The dataset is at state-date of the speech level. Treatment is defined at the date level.

or find common ground on important issues (Flynn, Nyhan and Reifler, 2017). It is, then, important, to understand if there is a link between my findings and this level of polarization.

To explore this connection, I study US Representatives Twitter feeds to see how the politicians interact with each other on the social network after a salient event[15]. Specifically, the focus is on how treated politicians communicate about their opponents compared to politicians unaffected by the event. I measure this by studying how each US Congressperson active on Twitter from 2009 to 2016 tweets about his/her counterpart after an MSE. First of all, I collect all the available tweets from US politicians active on the social network during this period. By using a regular expression, I then identify the tweets of each representative talking about another representative from the same state, but from the other party. I am able to select these tweets by searching for the account of the opponents or some specific words referring to him/her[16]. I then compute the sentiment score of each tweet by computing the number of negative words that are present in a tweet compared to the positive ones following the same procedure used before for computing my measure of rhetorical polarization.

In Table 2.7.2 I show how after an MSE the sentiment score of tweets of a treated representative referring to the opponent decreases compared to politicians not affected

[15] To study how the candidates of the different parties interact outside the House of Representatives with each other after a divisive shock it is crucial to understand what moves polarization (D'Amico and Tabellini, 2022).

[16] i.e., "Congressman + surname"; "Congresswoman + surname", "Rep + surname".

Table 2.7.2: Tweet about opponents after a salient event

	Sentiment on Tweets about Opponents		
	(1)	(2)	(3)
MSE	-0.1463**	-0.1457**	-0.1497**
	(0.0618)	(0.0580)	(0.0573)
Observations	12,458	12,458	12,458
Mean Outcome	0.5279	0.5279	0.5279
Week FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
State x Year FE	No	Yes	Yes
Controls	No	No	Yes

Notes: This table shows the effect of a mass shooting event on the sentiment score of a tweet. The outcome variable is score computed as total positive words minus negative ones normalized by the total number of words. I am using a subsample of all the tweets: the tweets that are referring to a member of the opposite parties. The main regressor is my treatment, mass shooting event. In column (1) I control for week and Congressional District FE, in column (2) I introduce State by year fixed effects and in column (3) I control for district and individual characteristics at baseline interact by year. Standard errors are clustered at congression district level.

by a shooting. In particular, controlling for specific characteristics of the representatives, and adding week, district and state by year fixed effects the estimates are stable and statistically significant at 5%. After an MSE, Representatives directly affected by the shock talk about their opposite members using more negative terms compared to not treated politicians. I interpret these results as an increase in the level of affective polarization which may motivate my previous results at least in part. Indeed, after such an event the conflict among politicians increases. This evidence suggests that after a trigger in a divisive topic there is a behavioral response from the politicians. They start to talk more in negative terms about their counterpart, and they attack the members of the opposite party more than before.

2.7.3 Politicians' strategic behavior - Theoretical Framework

Why does polarization on a divisive topic contaminate the other topics in different ways? To find an empirical answer to these questions is not easy. For this reason in this subsection I present a theoretical model which help to better understand and support my results. The idea of the model is based on the fact that politicians maximize their utility function by being re-elected. In order to be re-elected, politicians need consensus, and to do so, they need to know and follow, when possible, their electorate's positions on the different political topics. This model starts from the fact if, after these events, the electorate becomes more extreme than before it could be in the interest of a politician to follow the electorate ideological position not just as regarding the gun rights topic but also on other political issues. Specifically, my aim is to demonstrate that politicians become more polarized on topics where their electorate demonstrates a clear alignment. The underlying assumption is that politicians prefer to adopt a more polarized stance and express extreme positions on topics where their electorate is more homogeneously aligned. My theoretical framework derived by the idea of cultural and economic beliefs from Bonomi, Gennaioli and Tabellini (2021) and I interact it with a intra-party competition story (Canen, Kendall and Trebbi, 2021).

Political conflicts can today be divided into economic and cultural categories because these two factors often drive people's political beliefs and actions (Bonomi, Gennaioli and Tabellini, 2021). Economic conflicts typically arise from differences in wealth and power distribution. Cultural conflicts, on the other hand, stem from differences in values, beliefs, and attitudes towards issues such as immigration, race, and abortion. Economic and cultural values are often the underlying factors that shape political attitudes and behavior (Norris and Inglehart, 2019). From Bonomi, Gennaioli and Tabellini (2021) we know how individuals may respond to a salient shock on a particular topic. Indeed, following their model, a cultural shock (and mass shooting events may be considered as cultural shock) leads to increase the cultural conflict instead of the economic one. For this reason, since cultural identity gains more attention (and consequently importance) after such a divisive shock, the polarization on cultural topics increases, while the one on economic topics does not shift.

My theoretical framework leverages on this model, by adding the fact that in some topics voters assume binary positions in cultural topics, (e.g.: abortion, gun rights), while in others the discussion points are more. This model wants to show that when the topic presents a binary type of discussion after a cultural shock the probability to observe an increase in political polarization is higher because of intra-party competition. Politicians may strategically decide to polarize their opinion about cultural topic (following their own electorate), while on the economic topic they follow a median voter logic.

Following these works, I assume that the there are 2 different macro political identities: economical and cultural (Y_e and Y_c). There are three periods, $t \in \{0, 1, 2\}$. At time time $t = 0$ a cultural shock happens. Politicians then express their opinion on the topics Y_e and Y_c. There are two parties L and R. For each party $S \in \{L, R\}$ we have the following:

- Two politicians i_s and j_s who compete to become the leader of the party S
- A mass m_s of voters (we assume a continuum of total voters with mass 1) who are subscribed to the party and can select the leader of their party S (Primary election).

- There is also a mass of m_{sw} of voters who are not subscribed to any party.

The dynamic of the game is as follows:

t=0 Politicians express their opinion on the topics Y_e and Y_c.

t=1 m_L and m_R vote for the election of their party leader.

t=2 m_L, m_R and m_{sw} vote between the L leader and R leader to represent their state (or district)

Opinions are represented as points over a line $[0, 1]$ for each topic Y_k. For each Y_k, with $k \in \{e, c\}$, voters are distributed over the interval $[0, 1]$. We assume that the support of the marginal distribution over topic c is $X_c = \{0, 1\}$. Hence, voters can only adopt position 0 or 1 in terms of cultural topics. When expressing opinions, candidates try to maximize their expected utility to win both elections. When winning the first election, they get $u > \frac{1}{2}$. The utility of winning the first election is at least 1/2 because winning the election is also useful in terms of visibility. When winning the second one, they get additional utility of 1. The probability of winning election 1 for candidate i of party S, is a function of

- her own opinion (i_s) on each topic k, denoted by $y_k^{i_s}$
- opponent opinion (j_s) on each topic k, denoted by $y_k^{j_s}$
- the distribution of S voters opinions on k, denoted by F^S[17]

We denote this probability by

$$P_1^{i_s}(y^{i_s}, y^{j_s}, F^S) \tag{2.5}$$

where $y^{i_s} = (y_e^{i_s}, y_c^{i_s})$, $y^{j_s} = (y_e^{j_s}, y_c^{j_s})$ and F^S is the joint distribution over the topics Y_r, Y_c of all the voters. In the same fashion, the probability of winning election 2 (conditioning on the event of winning election 1) for candidate i_s of party S, is a function of

- her own opinion (i_s) on each topic k, denoted by $y_k^{i_s}$
- other party leader opinion (i_z) on each topic k (where i_z is the leader of the party $Z \in \{L, R\} \backslash S$)
- The distribution of all the voters on each topic k, denoted by F_k

We assume m_L vote for L and m_R vote for R in the second election. We denote this probability with

$$P_{2|1}^{i_s}(y^{i_s}, y^{i_z}, F) \tag{2.6}$$

[17] I assume that voters on cultural topics start in a more polarized position compared to economical ones, as suggested also in Bonomi, Gennaioli and Tabellini (2021).

Observe that this probability is equal to $P^{i_s}_{1\cap 2}/P^{i_s}_1$ (whenever $P^{i_s}_1 > 0$), where $P^{i_s}_{1\cap 2}$ is the probability of winning election 1 *and* election 2. Set it equal to zero when $P^{i_s}_1 = 0$. F includes the mass of swing voters as well. We assume that each swing voter deterministically votes for the candidate with the closest opinion in terms of Euclidean distance. Therefore, the expected utility of politician i_s of party S is:

$$P^{i_s}_1(1 - P^{i_s}_{2|1})u + P^{i_s}_1 \cdot P^{i_s}_{2|1}(u + 1) \tag{2.7}$$

which is equal to

$$P^{i_s}_1 \cdot u + P^{i_s}_{1\cap 2}. \tag{2.8}$$

Definition 1. *We say that two politicians i and j have a polarized opinion about topic Y_k whenever*

$$y^i_k = 0 \qquad y^j_k = 1 \tag{2.9}$$

Definition 2. *We say that two parties S and Z have polarized opinions about Y_k whenever*

$$y^{is}_k = 0 \qquad y^{iz}_k = 1 \tag{2.10}$$

for any politician i_s of party S and any politician i_z of party Z.

Theorem 1. *There exists an equilibrium where parties L and R have polarized opinions on cultural topics.*

In appendix I present the proof for this theorem, and in Figure 2.C.1 I present and discuss an example for better understand the theoretical model results. This example explains more concretely why the political polarization moves in some topics (cultural), while it does not in others (economic topics).

The theorem predicts polarization on cultural issues, meaning that opposing groups or individuals tend to take extreme positions on matters related to culture. More intuitevely, politicians anticipate polarization from their competitors within the party on cultural issues. Consequently, deviating from polarization would lead to their defeat in the first election. Since winning the initial election holds value for politicians, regardless of the outcome of the second election, they prefer to polarize in order to avoid losing votes. As a result, when we approach the second election, we observe politicians from different parties adopting extreme positions. However, this phenomenon may not occur in economic matters, as voters tend to hold less extreme positions on the subject, and politicians do not anticipate extreme stances from their competitors.

2.8 Policies and Congress composition

So far I show how a shock on a divisive topic impact the way politicians talk and interact with each other. I define this changes as an increase in the rhetorical polarization. Are there some consequences for the democratic process? In this last section, I study if and how a cultural shock, such as a mass shooting event, impact the democratic process. In particular, I focus on its influence on the discussion and implementation of policies in the House of Representatives. I shed some lights on this by showing how after a divisive event there is a decrease in the probability of passing a bill in the House of Representatives.

Table 2.8.1 shows how after an MSE, the probability of voting and passing a new law goes down by 4.6 percentage points. The result is significant at 1%. Controlling for the number of policies passed the previous week, and including also topic of the policy fixed effects, the result has unchanged. In column (2), with a more rigorous specification, we can see how after an MSE there is a reduction in the probability that a new law is passed in the House of Representatives by almost 4.7 percentage points compared to a normal day. It is relevant to note that divisive events make the democratic process weaker and slower by increasing the congressional gridlock. This result confirms the findings from the literature showing that polarization may generate division also in the policies proposed by the parties and impacting the congressional gridlock (Lee, 2022; Gordon and Landa, 2017).

The reasons behind this result could be found in the number of speeches that characterized these highly polarized days. In Table 2.A.12 I show that there is a positive correlation between the days following a shooting and the number of speeches and words used in the House of Representatives in the same period. These days are denoted by a higher number of speeches and words, meaning that the discussion is larger than in normal times.

Using the Voteview database, I can study the heterogeneity of the bills voted daily. Indeed, using the DW-nominate score, I can understand the leaning of a policy. The DW-nominate[18] give the score for the leaning of a policy going from -1 (ultra liberal policy) to 1 (ultra conservative policy). I generate different dummy variable depending on this score and I identify three different categories of policies[19]: liberal ($-1 <= DWscore <= -0.25$), , moderate ($-0.25 < DWscore < 0.25$) and conservative ($0.25 <= DWscore <= 1$). I interact these dummies with the MSE dummy to study if there is heterogeneity in my results. In Figure 2.8.1 I report the coefficients for the interaction of each dummy with the MSE. In the regression I include year-month,

[18] mid1 and mid2, see Lewis et al. (2019) for more details on how to compute these variables

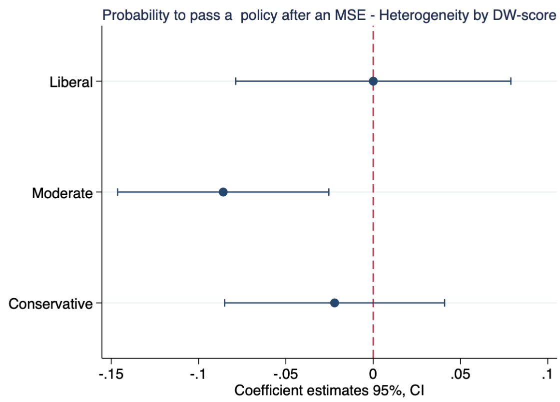
[19] I select these thresholds by following Poole and Rosenthal (2011).

Table 2.8.1: Probability to vote and pass a new policy the week after a MSE

	Probability to vote and pass a new law	
	(1)	(2)
MSE	-0.0463***	-0.0465**
	(0.0164)	(0.0225)
Observations	4,550	4,550
Year-month FE	Yes	Yes
Topic FE	Yes	Yes

Notes: This table shows the effect of mass shooting events on the probability to vote and pass a new policy.The outcome variable is a dummy equal to one if at time t a new policy is voted and it has been passed, 0 if it is voted, but not passed. In both specification I include year-month, and topic of the policy fixed effects. The dataset is a time series by date of the vote of a policy. Treatment is defined at the date level.

Figure 2.8.1: Probability to vote and pass a new policy after a MSE - Heterogeneity by Policy leaning



Notes: This figure shows heterogeneity in ideological by policy. The outcome variables is a dummy variable equal 1 if the policy voted has passed and 0 otherwise. Using DW-nominate score I identify three groups of policy: clearly liberal ($-1 <= DWscore <= -0.25$), clearly conservative ($0.25 <= DWscore <= 1$) and moderate ($-0.25 < DWscore < 0.25$). I interact the MSE dummy with these categorical variable controlling for year-month, and topic of the policy fixed effects. Standard errors are clustered at the congressional period level.

and topic of the policy fixed effects. Interestingly, it is possible to notice that the results of Table 2.8.1 is completely driven by the less extreme policies. In particular, by those policies with a DW-score between -0.25 and 0.25, meaning with a more moderate leaning.

To investigate how much this effect lasts, I run an event study comparing seven days before and ten days after an MSE (the highly polarized days). I study the evolution of the probability to vote and pass a policy on different topics as a function of the event time. Specifically, I run the following regression:

$$Passed_{d,t} = \sum_{j \neq -1} \alpha_j \mathbf{I}[j = t] + \sum_{k} \beta_k \mathbf{I}[k = yearweek] + \epsilon_{d,t} \tag{2.11}$$

Where $Passed^i_{d,t}$ is a dummy equal to 1 if a policy has been voted and passed the day d at event time t, while is 0 if the policy has been voted, but it has not passed. I include a full set of event time $\sum_{j\neq -1} \alpha_j \mathbf{I}[j = t]$. I omit the event period just before the mass shooting event. By including a full set of specific month of the year dummies ($\sum_k \beta_k \mathbf{I}[k = yearweek]$), I control non-parametrically for underlying seasonality trends, while by including a full set of year, month and day dummies I control non-parametrically for time trends.

In Figure 2.B.12, I report the event study for the probability to vote and pass a new policy. I study how this probability moves comparing seven days before and ten days after an MSE. Figure 2.B.12 highlights how in the seven days before the shooting there is not statistical difference between passing and not a new policy, while, after the event, this probability goes down significantly. I include time and topic of the policy fixed effects in this specification, Furthermore, I am controlling for the ideological position of the policies voted (DW-nominate, mid). Interestingly, following the policies not passed after a mass shooting, so during a period of higher polarization, and comparing them to the other policies not passed in a normal time, the first has even less probability of being voted and passed in the future. Table 2.8.2 shows exactly this results. Using a score similarity approach, I follow the policies over time. I consider a policy to be the same if it has a score similarity greater or equal to 80% and if the policy is voted again in the same congressional period of the first vote. Table 2.8.2 shows that these policies voted and not passed for the first time in a highly polarized period have 18 percentage point less probability of passing in the future compared to other policies not passed for the first time in normal times. Again, the results are completely driven by the moderate policies, while there is no effect for the ultra liberal or ultra conservative ones (column (2)). These results, with the previous ones, show that there is an impact of polarization also on policy-making, confirming in part the previous literature, but adding that the effects also have a long-lasting impact on the congressional gridlock. A policy voted and not passed for the first after a MSE needs to be modified more than another policy voted and not passed in normal times (far from a divisive event).

2.8.1 Congress Composition

In the previous subsection I show how after a divisive event, the probability to pass a new policy is negatively affected. This effect lasts not just in the short term, but also in the medium-long run. Indeed, those policies not passed after an MSE have a lower probability to be passed in the future compared to other policies that need more rounds to be approved by the House of Representatives. In this section I discuss whether contagious polarization affect also future congress composition. I study this

Table 2.8.2: Probability to vote and pass a new policy not passed after a MSE

	Probability to pass in the future	
	(1)	(2)
MSE	-0.1796***	-0.1718***
	(0.0370)	(0.0278)
MSE X extreme		-0.0144
		(0.1077)
Observations	3,528	3,528
Mean Outcome	0.5890	0.5890
Year-Month FE	Yes	Yes
Topic FE	Yes	Yes

Notes: This table compare policies not passed in the 20 days after a mass shooting to the other policies that have not passed in normale time.The outcome variable is a dummy equal to one if at time t a policy is voted and it has been passed, 0 if it is voted, but not passed. The treatment is a dummy indicator equal 1 if the policy in consideration has been voted and not passed after an MSE, and 0 if the policy has not been passed in normal time. In column (2) I show that the effect is complitely driven by the moderate policies. In both specification I include year-month, and topic of the policy fixed effects. The dataset is a time series by date of the vote of a policy. Treatment is defined at the date level. Standard errors are clustered at the congressional period level.

by investigating how the composition of the House of Representatives changes after such a divisive shock.

Previous literature showed that after an MSE the probability to vote for the Republican party decreases (Yousaf, 2021) and that there is an impact in the policy preferences of individuals in the states affected by the shock (Luca, Malhotra and Poliquin, 2020). Less is known about the composition of the politicians, and on the candidates characteristics. In particular, we don't know if after an MSE the probability to elect a Democrats or a Republicans is impacted and if there is an increase in the probability to have a more extremist candidate. For this analysis, I focus on a district-congressional period level dataset and I compare Congressional Districts (CDs) affected by an MSE to CDs not affected before and after the occurrence. In Table 2.A.13, I show that after a divisive event the probability to have a Republican or Democratic candidate does not change. Indeed, there is no statistically significant effect in either of my specifications. This contributes to the literature, by showing that, even if it seems that the electorate starts to vote less for the republican party (Yousaf, 2021) this effect it is just marginal and it is not sufficient to change the composition of the House of Representatives.

On the other hand, running the same analysis using as outcome variable a dummy taking value 1 when the elected candidate is an extreme one and 0 otherwise, there is a statistically significant effect. In Table 2.8.3 I show exactly these results. Using the DW-Nominate score (Lewis et al., 2019), I identify as extreme candidate (Han and Brady, 2007) one with a score between 0.5 and 1 (ultra conservative) or -0.5 and

Table 2.8.3: Probability to have a more extreme candidate after a MSE

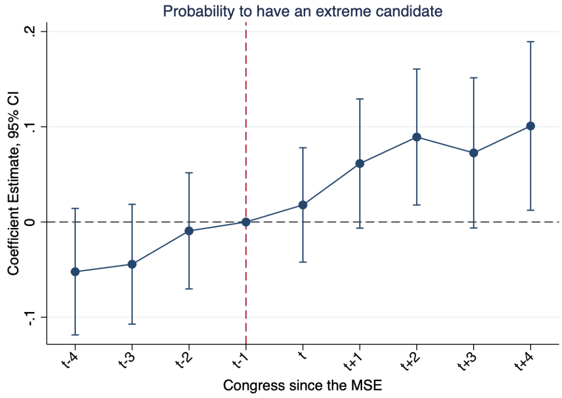
	Probability of electing extreme candidate			
	TWFE	TWFE	BJS	BJS
	(1)	(2)	(3)	(4)
MSE	0.0660**	0.0726**	0.0732**	0.0727**
	(0.0298)	(0.0287)	(0.0317)	(0.0288)
Congress FE	Yes	Yes	Yes	Yes
Congressional district FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean Outcome	0.2954	0.2954	0.2954	0.2954
Observations	3,695	3,695	3,695	3,695

Notes: This table shows the effect of mass shooting events on the probability to have a more extreme US Representative in the future.The outcome variable is a dummy equal to one if the US Representative is an extreme candidate identified using DW Nominate. In the first two columns I present TWFE estimations controlling for Congressional peiod and Congressional District FEs and including control variables. In the last two columns I show the same results by using Borusyak, Jaravel and Spiess (2021) estimator. The standard errors are clustered at the Congressional District level.

-1 (ultra liberal). Using a difference-in-differences approach I compared candidate in CDs with and without a MSE before and after the event. In the congressional period after the shock the probability to have a more extreme representative increases by 7 percentage points in all my specification. In the most complete specification I control for pre-treatment socio-economic characteristics of the CD, for the characteristics of the incumbent candidate and I include congressional period and congressional district fixed effects. The results are robust to the new Borusyak, Jaravel and Spiess (2021) estimator (column (3) and (4)). Running an event study approach, I show in Figure 2.8.2 that the effects are statistically persistent for 4 congressional periods after the treatment. Using again the Borusyak, Jaravel and Spiess (2021) estimator, I confirm my TWFE event study results in Figure 2.B.13.

These evidences show that a divisive event such as an MSE, have long lasting effects on the candidates selection. Even if the effects on the rhetorical polarization seem to disappear in the short term, places affected by an MSE are electing more extreme candidates while the probability to elect a candidate from a party or the other does not change. This means that there is a change in the selection of the candidates running for the Primary elections (intra-party polarization Canen, Kendall and Trebbi (2021)). Further research should investigate this more by studying how a divisive shock impact the Primary election and if the election of more extreme candidates is supply or demand driven.

Figure 2.8.2: Probability to have a more extreme candidate after a MSE - Event Study



Notes: This figure shows event study estimates for the probability to elect an extreme candidate before and after a divisive shock (MSE). The outcome variables is a dummy variable equal 1 if the candidate is extremist and 0 otherwise identified using DW-nominate score. I control for pre-treatment socio-economic characteristics of the CD, for the characteristics of the incumbent candidate and I include congressional period and congressional district fixed effect. Standard errors are clustered at the congressional district level.

2.9 Conclusion

Political polarization has reached unprecedented levels in Western democratic countries, especially in the United States. The existing literature attributes this phenomenon to various political, economic, and social factors, some of which have long-term effects, while others impact polarization temporarily. Previous research has primarily approached political polarization as a unified concept, focusing on its evolution over the medium to long term. However, it is evident that polarization varies across different political topics at any given moment. Furthermore, it is important to understand how different political issues intersect and shape polarization is essential. By exploring the interconnections of these topics, we can gain insights into how they collectively contribute to the overall level of polarization.

In this paper, I show that after a salient shock on a relevant and divisive political topic, such as gun rights for the US, there is a causal consequence of politicians' way of speaking, which I define as rhetorical polarization. The study measures political polarization by analyzing the official speeches of US Representatives, employing text analysis techniques. This measure captures the contrast in the way individuals from different political parties communicate about the same issue.

By examining the occurrence of mass shootings as a source of variation and trigger to the polarization on the gun rights topic. The paper employs a dynamic difference-in-differences design, comparing the rhetorical polarization of politicians from states directly affected by mass shootings with those not impacted before and after the occurrence.

The findings demonstrate that after a mass shooting event, politicians' rhetorical polarization increases not only on gun-related topics but also on other unrelated subjects, such as social policy, war and defense, environment, and justice. This suggests that polarization is contagious and should be understood as a multidimensional phenomenon, especially in the short term. Interestingly, the results are driven by those MSEs which involved more fatalities, meaning that the salience of the events matters for generating contagious effects.

Using an event study approach, I show that there is no statistical difference between treated and control groups in the months (and weeks) leading up to the mass shooting. Furthermore, the effect lasts for at least one month of discussion after the shooting.

The paper investigates and discusses potential mechanisms underlying these findings, focusing on the communication patterns of politicians after these salient events. The study develops a theoretical framework to shed light on why cultural topics may elicit stronger reactions compared to economic issues.

After such events, the probability that an extreme candidate speaks is not statistically different from a moderate one.

Moreover, I proxy for affective polarization using the Twitter feed of the US Representatives. After an MSE, the treated politicians are referring to their opponents using more negative terms than before. This evidence suggests that, at least in part, my findings may be explained by an increase in the affective polarization among politicians. These findings contribute also to the sociology literature on the affective polarization, showing that this phenomenon may be present among the elites as well.

In addition to examining the immediate effects, the paper explores the consequences of divisive events on policy-making. It demonstrates that after such events, the probability of passing new policies decreases, confirming previous research that links polarization to congressional gridlock. Using a similarity score index, I follow these policies over time, showing that they have even less probability of passing in the future compared to other policies that did not pass in normal times. These findings indicate that divisive events may have enduring effects on policy-making.

Finally, the paper reveals that mass shooting events can impact the future composition of the House of Representatives. In the Congressional Districts affected by such events, there is a higher probability of electing an extreme candidate in the future, regardless of party affiliation. This suggests that the effect is not specific to Democrats or Republicans but rather leads to the election of more extreme candidates compared to the previous representatives of those districts.

In conclusion, this paper demonstrates that a salient shock on a divisive topic can contribute to shifts in political polarization. Furthermore, political polarization exhibits contagious properties across different topics, leading to a trickle-down effect on other political issues. The study highlights the multidimensional nature of political polarization, as not all topics experience an increase in partisanship. These findings are significant as they have long-lasting implications for policy-making and the future composition of Congress. Overall, the results emphasize that even random and infrequent events can play a crucial role in the polarization of politicians.

Appendices

2.A Tables

Table 2.A.1: Polarization on Social Policy Topic after MSE

	Polarization on Social Policy			
	(1)	(2)	(3)	(4)
MSE	0.0028***	0.0028***	0.0026**	0.0044
	(0.0010)	(0.0010)	(0.0010)	(0.0032)
Mean Outcome	0.0308	0.0308	0.0308	0.0308
Observations	20,997	20,997	20,974	20,979
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the social policy topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the social policy topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by year such as: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (3) I include seasonality trends. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table 2.A.2: Polarization on Economy Topic after MSE

	Polarization on Economy			
	(1)	(2)	(3)	(4)
MSE	0.0010	0.0011	0.0009	-0.0028*
	(0.0006)	(0.0007)	(0.0007)	(0.0015)
Mean Outcome	0.0330	0.0330	0.0330	0.0330
Observations	20,997	20,997	20,974	20,974
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the economy topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the economy topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by year such as: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (3) I include seasonality trends. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table 2.A.3: Polarization on Environment Topic after MSE

	Polarization on Environment			
	(1)	(2)	(3)	(4)
MSE	0.0020**	0.0021**	0.0018**	0.0026***
	(0.0008)	(0.0008)	(0.0008)	(0.0009)
Mean Outcome	0.0219	0.0219	0.0219	0.0219
Observations	20,997	20,997	20,974	20,974
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the environment topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the environment topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by year such as: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (3) I include seasonality trends. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table 2.A.4: Polarization on War and Defense Topic after MSE

	Polarization on War and Defense			
	(1)	(2)	(3)	(4)
MSE	0.0025***	0.0025***	0.0025***	0.0034*
	(0.0009)	(0.0008)	(0.0009)	(0.0018)
Mean Outcome	0.0272	0.0272	0.0272	0.0272
Observations	20,997	20,997	20,974	20,974
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the war and defense topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the war and defense topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by year such as: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (3) I include seasonality trends. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table 2.A.5: Polarization on Justice and Law Topic after MSE

	Polarization on Justice and Law			
	(1)	(2)	(3)	(4)
MSE	0.0015*	0.0014*	0.0027	0.0031
	(0.0008)	(0.0007)	(0.0022)	(0.0035)
Mean Outcome	0.0477	0.0477	0.0477	0.0477
Observations	20,997	20,997	20,974	20,974
Date of Speech FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Seasonality Trends	No	No	Yes	Yes
State x Year FE	No	No	No	Yes
Controls x Congress	No	Yes	Yes	Yes

Notes: This table shows the effect of mass shooting events on the justice and law topic polarization. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the justice and law topic, at time t. I include date of the speech, and state fixed effects in column 1. In column (2) I include control variables at baseline interacted by year such as: log population, share male, share white, share black, share Hispanic, share unemployed, days before the Primary elections. In column (3) I include seasonality trends. Standard errors are clustered at the state congressional level. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

2.A.1 Different Time Windows

Before showing the event study and that the parallel trends assumption is satisfied, it is important to show the same results presented before using shorter time windows in order to understand if the levels in political polarization are mainly impacted immediately after an MSE and that the effect is stronger in the short term. To study this, I run the same specification discussed before, but using shorter time windows. This method allows me to exploit all the multiple treatments happening in the same Congressional period and see if the results remain the same in terms of magnitude and significance level. In Table 2.A.6 I report the estimates for these different dynamic difference-in-differences. From these coefficients it is possible to state that the effect is stronger immediately after the shock and that it then decreases over time. In the month after an MSE, the polarization in the Gun Rights polarization increases by 0.36 percentage points at 1% confidence interval, while 1 semester and 1 year after it increases respectively by 0.4pp and 0.26pp respectively. I present the results using the most complete specification including date of the speech FE, state by year fixed effects, seasonality trends and my battery of controls.

Table 2.A.6: Polarization on Gun Right Topic after MSE - Different Time Windows

	Polarization on Gun Rights		
	(1)	(2)	(3)
MSE month window	0.0036***		
	(0.0011)		
MSE semester window		0.0040***	
		(0.0014)	
MSE year window			0.0026***
			(0.0009)
Mean Outcome	0.0065	0.0065	0.0065
Observations	20,997	20,997	20,997
Date of Speech FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Seasonality Trends	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Controls x Congress	Yes	Yes	Yes

Standard errors are clustered at the State level
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the effect of mass shooting events on the guns' Topic Polarization. The outcome variable is computed as the absolute difference between the Republican Position and the Democratic Position from state s, on the guns Topic, at time t. I control for date of the speech and state fixed effects. I include state linear trends and control at baseline interacted with year fixed effects as well. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting till the end of the time window (1 month, semester or year after the MSE, respectively column(1), column (2) and column (3)).

Table 2.A.7: Polarization on Macro Topics after MSE - Borusyak, Jaravel and Spiess (2021) estimator

	(1) Gun Rights	(2) Social Policies	(3) Economy	(4) Environment	(5) War and Defense	(6) Justice and Law
MSE	0.0004**	0.0048***	0.0021	0.0023**	0.0047**	0.0030*
	(0.0001)	(0.0009)	(0.0016)	(0.0004)	(0.0023)	(0.0016)
Date of Speech FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,997	20,997	20,997	20,997	20,997	20,997

Notes: This table shows the effect of mass shooting events on the level of polarization of the different macro topics. The outcome variable are respectively the standardized levels of polarization in the 5 macro topics presented before (social policy, economy, environment, war and defense and justice) and the gun rights topic . These coefficients are generated using the new machinery suggested by Borusyak, Jaravel and Spiess (2021) for controlling for the fact that treatment varies across times (staggered time). I control for date of the speech and state fixed effects. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table 2.A.8: Polarization on Macro Topics after MSE - Standard errors clustered at date of the congressional meeting

	(1) Gun Rights	(2) Social Policies	(3) Economy	(4) Environment	(5) War and Defense	(6) Justice and Law
MSE	0.0015**	0.0026*	0.0009	0.0021*	0.0025**	0.0024
	(0.0006)	(0.0016)	(0.0012)	(0.0013)	(0.0012)	(0.0020)
Date of Speech FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,997	20,997	20,997	20,997	20,997	20,997

Notes: This table shows the effect of mass shooting events on the level of polarization of the different topics. The outcome variable are respectively the levels of polarization in the 5 macro topics presented before (social policy, economy, environment, war and defense and justice) and the gun rights topic. These coefficients are generated using the prefferred specifications controlling for the date of the speech, and state fixed effects, and for the seasonality trends and including the battery of controls. Standard errors are clustered at day of the congressional meeting level. The dataset is a state by date of congressional meeting panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table 2.A.9: Polarization on Macro Topics after MSE - Standard errors clustered at date of the congressional meeting and state level

	(1) Gun Rights	(2) Social Policies	(3) Economy	(4) Environment	(5) War and Defense	(6) Justice and Law
MSE	0.0015***	0.0026**	0.0009	0.0021*	0.0025**	0.0024
	(0.0005)	(0.0012)	(0.0009)	(0.0012)	(0.0012)	(0.0019)
Date of Speech FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,997	20,997	20,997	20,997	20,997	20,997

Notes: This table shows the effect of mass shooting events on the level of polarization of the different topics. The outcome variable are respectively the levels of polarization in the 5 macro topics presented before (social policy, economy, environment, war and defense and justice) and the gun rights topic. These coefficients are generated using the prefferred specifications controlling for the date of the speech, and state fixed effects, and for the seasonality trends and including the battery of controls. Standard errors are clustered at day of the congressional meeting and state level. The dataset is a state by date of congressional meeting panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period.

Table 2.A.10: Specific words used by Republicans and Democrats about guns

Control		Treated	
Dem	Rep	Dem	Rep
victims	illegal	suspected	stopped
silence	prohibited	buy	attack
commonsense	list	walk	shot
mass	sale	loophole	murdered
killed	law	purchase	violent
deadly	ban	weapon	prayers
tragedy	shows	prevent	thoughts
children	criminal	ban	happened
violent	dealers	legally	killing
innocent	used	crime	taken

Notes: This table shows the specific words used by treated and control republican and democrat speakers about the guns topic. Using the ALC embedding tool I identify the most common words used around the word: "gun".

Table 2.A.11: Specific words used by Republicans and Democrats about second amendment

Control		Treated	
Dem	Rep	Dem	Rep
act	liberty	gun	constitution
legislation	freedom	legislation	protected
issue	exercise	firearms	fundamental
must	fundamental	issue	liberty
bill	protecting	reason	citizens
strongly	arms	case	protecting
provision	obligation	commonsense	obligation
colleagues	responsability	case	freedom
support	property	act	liberties
gun	bear	control	defend

Notes: This table shows the specific words used by treated and control republican and democrat speakers about the second amendment. Using the ALC embedding tool I identify the most common words used around the bigram: "second amendment".

Table 2.A.12: Number of Words and Speeches the day after a MSE

	(1) Number of Words	(2) Number of Speeches
MSE	272.2040***	3.1618***
	(14.9592)	(0.0585)
Mean_outcome	50361.99	81.9430
Year-Month FE	Yes	Yes
Observations	4,550	4,550
Adjusted R^2	0.196	0.317

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table shows the effect of mass shooting events on the number of speeches and words. I include year-month fixed effects. The dataset is a time series by date of the speech. Treatment is defined at the date level.

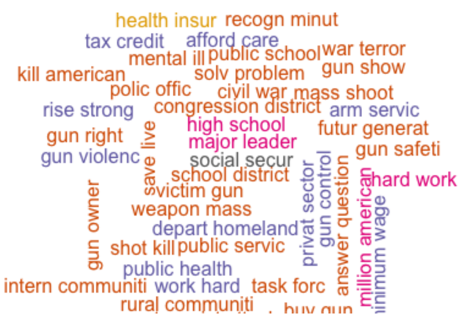
Table 2.A.13: Probability to have a Representatives of one of the two parties after a MSE

	Probability of electing Democratic candidate			
	TWFE (1)	TWFE (2)	BJS (3)	BJS (4)
MSE	-0.0005	0.0159	-0.0503	-0.0323
	(0.0306)	(0.0299)	(0.0342)	(0.0323)
Congress FE	Yes	Yes	Yes	Yes
Congressional district FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Mean Outcome	0.4858	0.4858	0.4858	0.4858
Observations	3,695	3,695	3,695	3,695

Notes: This table shows the effect of mass shooting events on the probability to have a Democratic US Representative in the future.The outcome variable is a dummy equal to one if the US Representative is from the Democratic party. In the first two columns I present TWFE estimations controlling for Congressional peiod and Congressional District FEs and including control variables. In the last two columns I show the same results by using Borusyak, Jaravel and Spiess (2021) estimator. The standard errors are clustered at the Congressional District level.

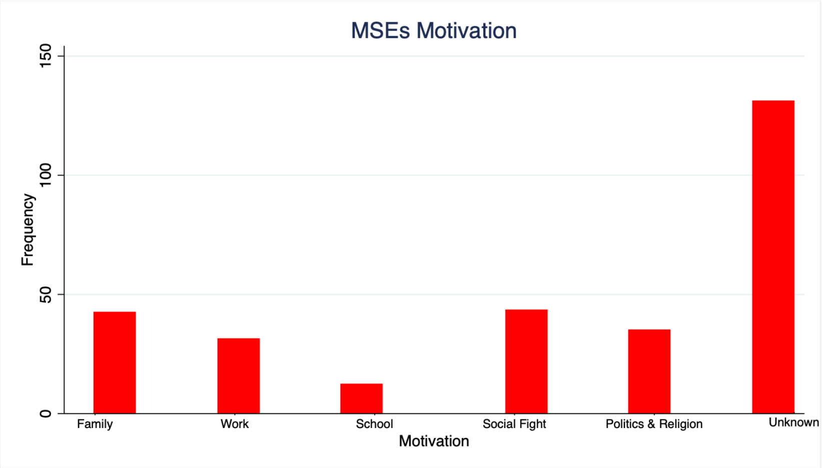
2.B Figures

Figure 2.B.1: Word Cloud - Gun Bigrams



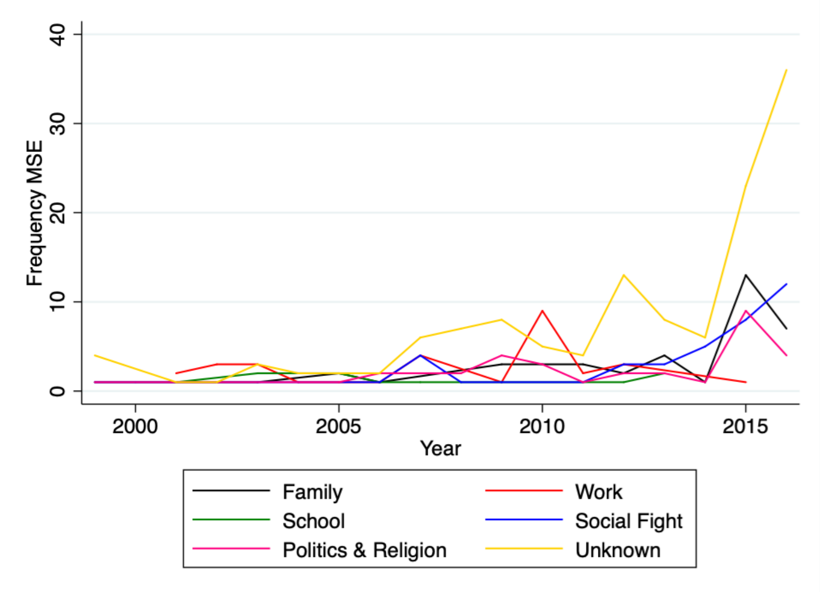
Notes: This figure shows a word-cloud with the 50 bigrams that have the highest weight for the gun rights topic.

Figure 2.B.2: Motivation of mass shooting events



Notes: This figure shows the frequency of the mass shooting events' motivations. The motivation are assigned by the FBI.

Figure 2.B.3: Variation over years of mass shooting events



Notes: This figure shows the variation over years of the mass shooting events.I plot this variations by motivation.

2.B.1 Sentiment Analysis and Topic Model

Before applying the sentiment analysis and topic models to my corpus of speeches I apply the pre-processing tranformation to normalize the text (Ash and Hansen, 2023). I, first, remove punctuation, hyphens, apostrophes, numbers, "stop-words" (common words in English). At this point, after having severely reduced the number of words, I transform each word to their stems following the Porter algorithm (Porter, Boulton and Macfarlane, 2002). Finally, I remove the rare and common words by applying a TF-IDF (term frequency-inverse document frequency). After these cleaning procedures

I end up with a corpus composed by each cleaned speech presenting words that appear at least 100 times and in at least 10 documents. In the next section, I will explain more in details these procedures and the other tools I implement for constructing my measure of rhetorical polarization.

The paper uses a dictionary-based sentiment analysis to identify negative and positive words in a speech. The dictionary-based methods find the sentiment of a piece of text by adding up the individual sentiment scores for each word in the text. There are various ways and dictionaries for evaluating the opinion or emotion in texts. In this work, I use two different lexicons together: "NRC" (Mohammad and Turney, 2013) and "BING" (Liu and Zhang, 2012). These lexicons are based on unigrams, i.e., single words, and they contain many English words. A score for positive/negative sentiment is assigned to each word. Not all the words are in the lexicons because of the neutrality of some words. Following this procedure, I assign a quantitative measure to each speech based on the number of positive and negative words in the speech. I then correct for some specific language constructions[20]

To understand the topic of a speech I exploit two different topic models: LDA and STM. These two models are very similar to each other as regarding the technical procedure. Both these techniques are generative probabilistic model for collections of discrete data such as text corpora. They are three-level hierarchical Bayesian model, in which each item of a collection is modeled as a finite mixture over an underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities. In the context of text modeling, the topic probabilities provide an explicit representation of a document (in this case, a document is a single speech). The intuition behind is that a distribution of topics can describe a distribution of words that can explain each speech and each topic. STM is particularly useful for this work because it employs metadata about documents (such as the name of the author, the date in which the document was produced or the party) to improve the assignment of words to latent topics in a corpus. STM is a mixture model, where each document can belong to a mixture of the designated k topics. In choosing the STM model or assessing the goodness of fit, two measures can be used: semantic cohesion and exclusivity (Roberts, Stewart, Tingley, Lucas, Leder-Luis, Gadarian, Albertson and Rand, 2014). A topic is cohesive when high-probability terms for a topic occur together in documents. A topic is exclusive if the top words of the topic are not likely also to be top words in other topics. This model is also handy for the very high-quality R package available for implementing it. Moreover, this model does not need any predetermined decisions, but it can understand the number of topics presented in the documents. This allows

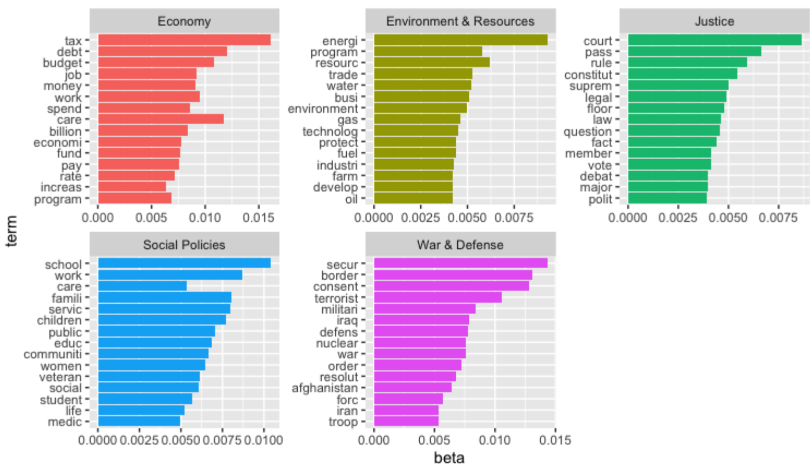
[20]When some negative terms such as "not" appears in front of a negative or positive word, the sentiment is reverted.

me to identify the most discussed topics from all speeches.

Figure 2.B.4: Word Clouds of Negative and Positive - Sample

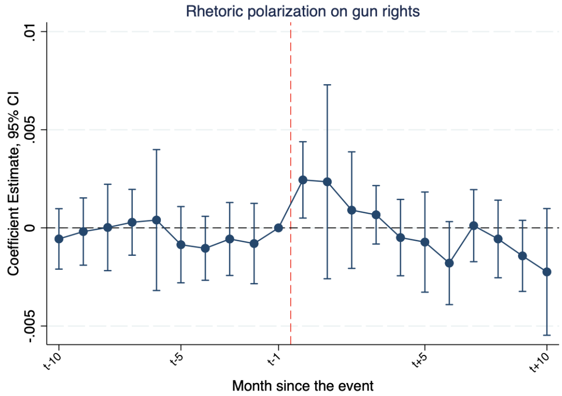
Notes: This figure shows a word-cloud representing a sample of negative-positive words. In blue I show the negative words assigned by my algorithm and in red the positive ones.

Figure 2.B.5: Topic Model - LDA



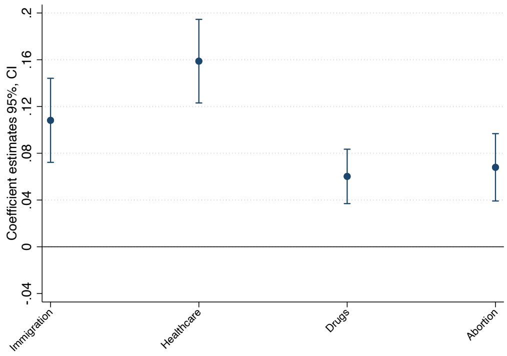
Notes: This figure shows the results of an LDA topic model run on the congressional speeches. I identify the 5 Macro topics: Economy, Environment, Justice and Law, Social Policies and War and Defense.

Figure 2.B.6: Polarization on Gun Right Topic after MSE, Event Study Month level (TWFE)

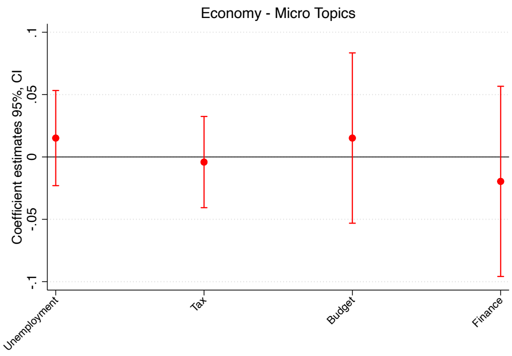


Notes: This figure reports the event study estimates for the gun righst topic at the month level. The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. The omitted category is the month leading up to the shock. Standard errors are clustered at the state level.

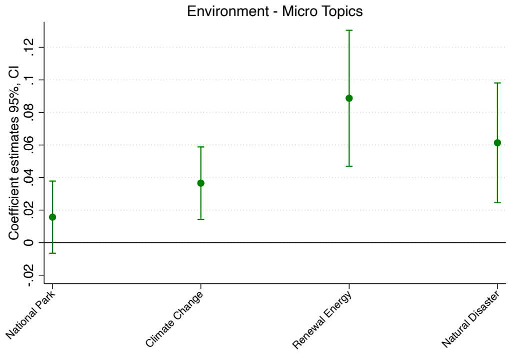
Figure 2.B.7: (Std) Polarization on the different Micro Topics and MSE



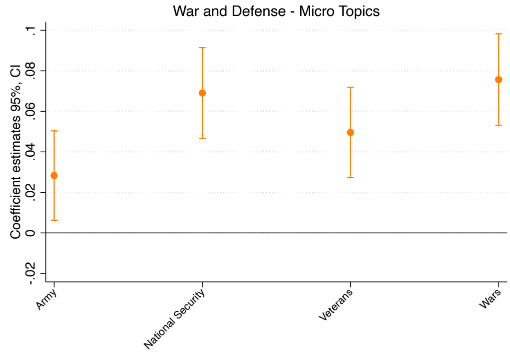
(a) *Social policy*



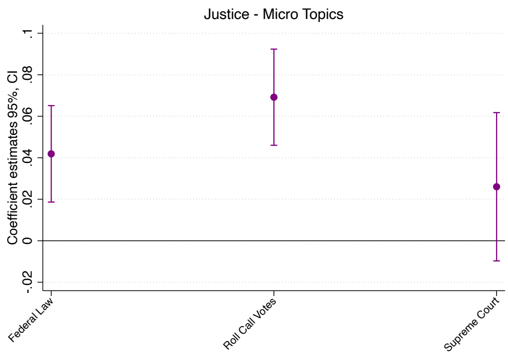
(b) *Economy*



(c) *Environment*



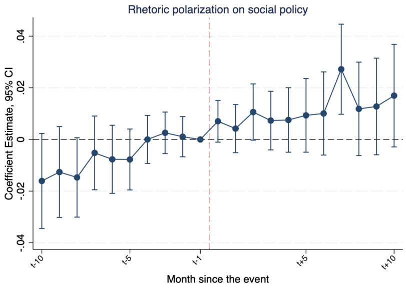
(d) *War and defense*



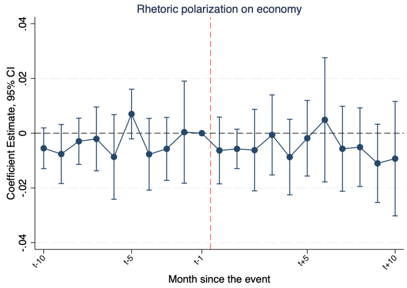
(e) *Justice and Law*

Notes: This figure shows the effect of mass shooting events on the micro topics level of polarization divided by the 5 macro topic. The outcome variable is computed as the absolute difference between the Republican score and the Democratic score from state s, on the a topic identified using a Structural Topic Model, at time t. To make interpreation of the coefficients easier I standardized the outcome variables. I show coefficients derive from my baseline specification including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. The dataset is a state by date of speaking panel. Treatment is defined at the date level. A state is considered treated in a given date after the first shooting happened till the end of the Congressional period. Standard errors are clustered at state level.

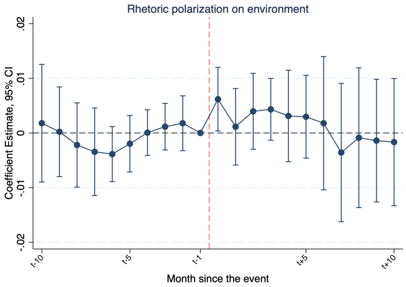
Figure 2.B.8: Polarization on the different Macro Topics and MSE, Event Study



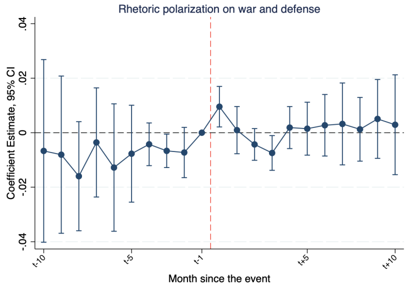
(a) *Social Policy*



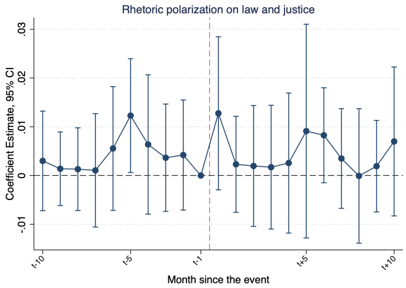
(b) *Economy*



(c) *Environment*



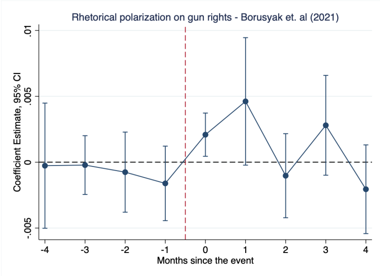
(d) *War and Defense*



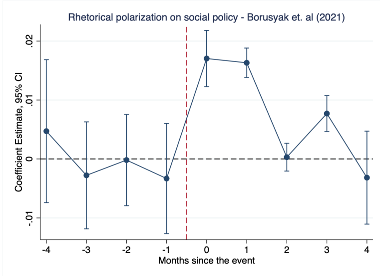
(e) *Justice and Law*

Notes: This figure reports the event study estimates for the 5 Macro topics at the month level. The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. The omitted category is the month leading up to the shock. Standard errors are clustered at the state level.

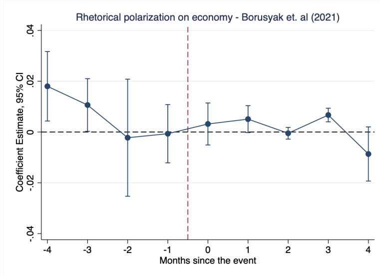
Figure 2.B.9: Event Study - Borusyak et. al. (2021)



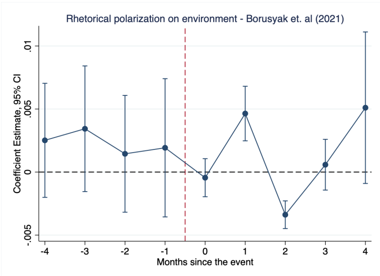
(a) *Gun rights*



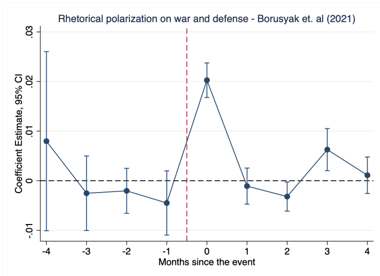
(b) *Social policy*



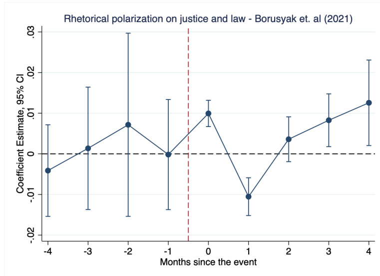
(c) *Economy*



(d) *Environment*



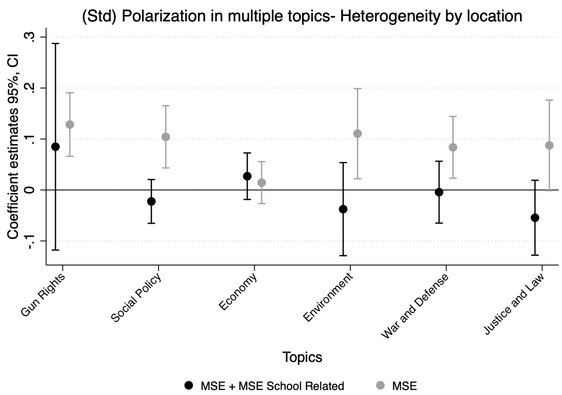
(e) *War and Defense*



(f) *Justice and Law*

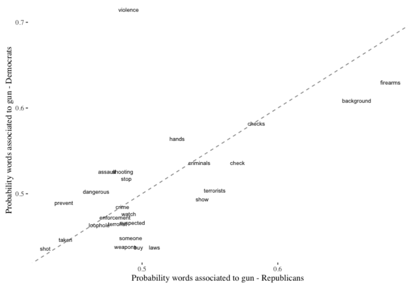
Notes: This figure reports the event study estimates for the 5 Macro topics at the month level using the Borusyak, Jaravel and Spiess (2021) machinery for taking into account the time heterogeneity of the treatment. The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects. Standard errors are clustered at the state level.

Figure 2.B.10: Heterogeneity by saliency - School related

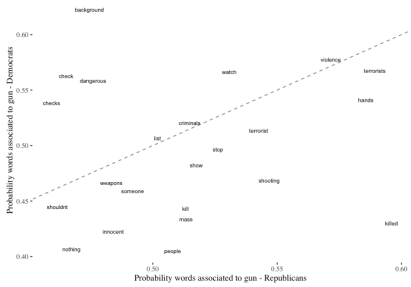


Notes: This figure reports heterogeneity by saliecy. The outcome variables are respictively the standard level of rhetorical polarization on the gun rights, social policy, economy, environment, war and defense, and justice topics. I interacted my treatment witha dummy identifiying those mass shooting events school related. The plot is generated by including date of the speech and state fixed effects, controlling for a battery of time variant control variables and time invariant controls interacted with congress fixed effects.

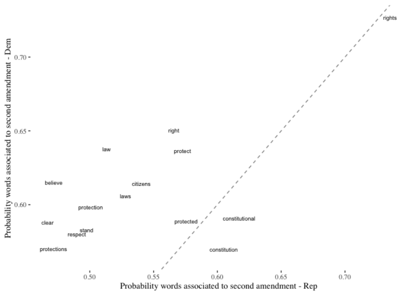
Figure 2.B.11: Cosine similarity associated to Gun Violence and Second Amendment



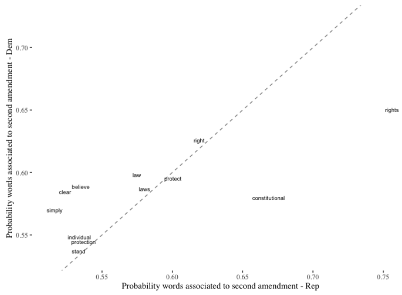
(a) *Gun Violence - Control Group*



(b) *Gun Violence - Treated Group*



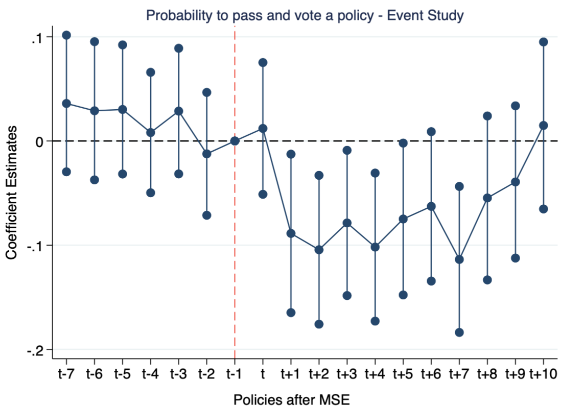
(c) *Second Amendment - Control Group*



(d) *Second Amendment - Treated Group*

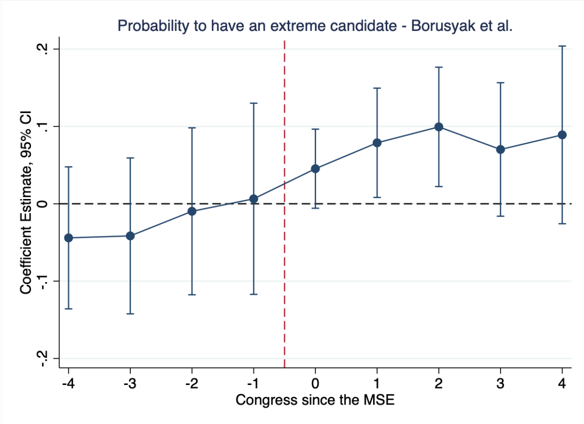
Notes: These graphs show the words with the highest cosine similarity associated to the focal bigrams "gun violence" and "second amendment". I plot on the y axis the probability assigned to the democratic candidates and in the x axis the one assigned to the republican party. The dashed grey line is a 45 degree line. For each focal bigrams I plot one graph for the control group and one for the treated group.

Figure 2.B.12: Probability to vote and pass a new policy



Notes: This figure shows event study for the probability to vote and pass a new policy. I am comparing the probabiity to pass a new policy before and after a mass shooting event. I focusing on a 20 congressional meeting days window. The omitted category is the last congressional meeting before the shooting.The outcome variable is a dummy equal to one if at the congressional meeting day t a new policy is voted and it has been passed, 0 if it is voted, but not passed. I include year-month, and topic of the policy fixed effects. The dataset is a time series by date of the vote of a policy. Treatment is defined at the date level.

Figure 2.B.13: Probability to have a more extreme candidate after a MSE - Event Study, Borusyak et. al



Notes: This figure shows event study estimates for the probability to elect an extreme candidate before and after a divisive shock (MSE). I use the Borusyak, Jaravel and Spiess (2021) command for accounting the heterogeneity in time of my treatment. The outcome variables is a dummy variable equal 1 if the candidate is extremist and 0 otherwise identified using DW-nominate score. I control for pre-treatment socio-economic characteristics of the CD, for the characteristics of the incumbent candidate and I include congressional period and congressional district fixed effect. Standard errors are clustered at the congressional district level.

2.C Theoretical Model - Proof and Example

Proof. Consider party S such that $F_c^S(0) = 1$, where F_c^S is the marginal distribution of voters subscribed to party S over the topic c. Now, suppose two candidates s_1 and s_2 are competing for the leadership of party S while z_1 and z_2 are competing for the leadership of party $Z \in \{L, R\} \setminus S$. Assume $y_c^{s_2} = 0$ and $y_c^{z_1} = y_c^{z_2} = 1$. First, we prove that $y_c^{s_1} = 1$ cannot be optimal for player s_1. In fact, observe that the minimum distance between s_1 position (i.e., opinion) and any S voter's position is at least one. The maximum distance, instead, between s_2 position and any S voter's position is less than one. Therefore, $P_1^{s_1} = 0$, and since by definition $P_{1\cap 2}^{s_1} \leq P_1^{s_1}$, we have that s_1 utility is 0. A profitable deviation is $(y_c^{s_1}, y_e^{s_1}) = (y_c^{s_2}, y_e^{s_2})$. In fact, in this case, $P_1^{s_1} = \dfrac{1}{2}$ and the expected utility is $P_1^{s_1} \cdot u + P_{1\cap 2}^{s_1} > 0$. Therefore, we must have $y_c^{s_1} < 1$. Hence, assume $y_c^{s_1} \in (0, 1)$. Suppose we are in equilibrium. Then, $P_1^{s_1} = P_1^{s_2} = \dfrac{1}{2}$,[21] and clearly $y_e^{s_1} \neq y_e^{s_2}$ (otherwise $P_1^{s_2} = 1$). Moreover, $P_{1\cap 2}^{s_1} = P_{1\cap 2}^{s_2}$ (otherwise either s_1 wants to imitate s_2 or vice-versa). Observe that $P_{1\cap 2}^{s_1} = P_{1\cap 2}^{s_s} \in \{0, 1/4, 1/2\}$ in equilibrium, as $P_{2|1}^{s_1} \in \{0, 1/2, 1\}$ and $P_1^{s_1} = \dfrac{1}{2}$. Therefore, first suppose $P_{1\cap 2}^{s_1} = P_{1\cap 2}^{s_2} = 0$. Then, s_2 can set $y_e^{s_2} = y_e^{s_1}$, so that s_2 is closer to any S voter than s_1, and hence $P_1^{s_2} = 1$. Since $P_{1\cap 2}^{s_2}$ is unchanged, this is a profitable deviation, a contradiction. Now, assume $P_{1\cap 2}^{s_1} = P_{1\cap 2}^{s_2} = \dfrac{1}{4}$. Again, change s_2 position on topic r, so that $y_e^{s_2} = y_e^{s_1}$. As before, $P_1^{s_2} = 1$. In the worst case scenario, this implies $P_{1\cap 2}^{s_2} = 0$. Yet,

$$1 \cdot u + 0 > \frac{1}{2} \cdot u + \frac{1}{4}$$

since $u > \dfrac{1}{2}$. Therefore, we still have a profitable deviation. Finally, assume $P_{1\cap 2}^{s_1} = P_{1\cap 2}^{s_2} = \dfrac{1}{2}$. In equilibrium, it is not a profitable deviation for s_2 to imitate s_1 on topic r. Since the expected utility that s_2 obtain when setting $y_e^{s_2} = y_e^{s_1}$ is $u + \tilde{P}_{1\cap 2}^{s_2}$ (where $\tilde{P}_{1\cap 2}^{s_2}$ is the new probability of winning both elections when imitating s_1 on topic r), we must have that

$$1 \cdot u + \tilde{P}_{1\cap 2}^{s_2} < \frac{1}{2} \cdot u + P_{1\cap 2}^{s_2},$$

which implies

$$u < 2 \cdot (P_{1\cap 2}^{s_2} - \tilde{P}_{1\cap 2}^{s_2}).$$

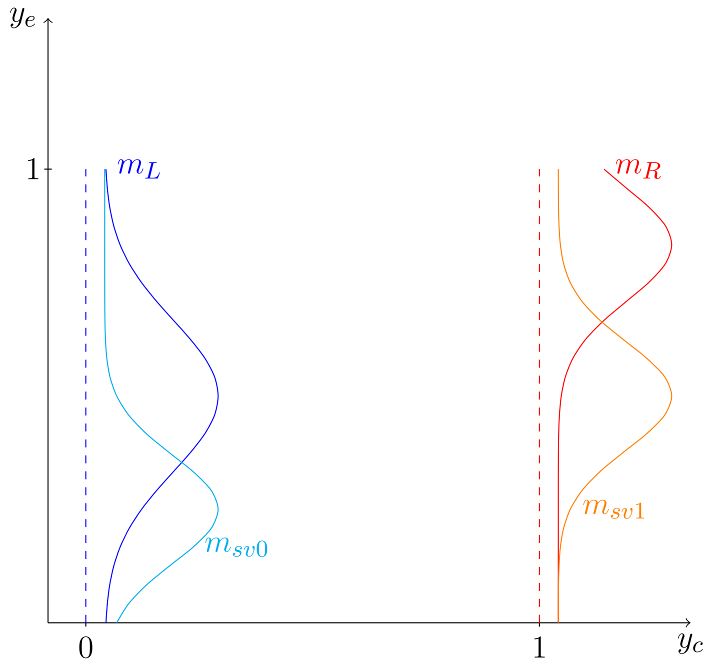
and therefore we must have $\tilde{P}_{1\cap 2}^{s_2} = 0$ and $P_{1\cap 2}^{s_2} = \dfrac{1}{2}$. Since the swing voters w such that $y_c^w = 1$ will vote for the leader of party Z in case s_2 win the first election, and

[21] Since there are two candidates and voters' choice is deterministic, we must have $P_1^i \in \{0, 1/2, 1\}$. If $P_1^i = 1$, then $P_1^j = 0$ (where j is i's competitor), and j could increase this probability by assuming i's position, hence we would not be in equilibrium.

$P^{s_2}_{2|1} = 1$, we must have that the mass of voters v such that $y^v_c = 0$ is strictly greater than $\frac{1}{2}$. But then, setting $y^{s_2}_e = y^{s_1}_e$ will increase $P^{s_2}_1$ to 1 and since the mass of voters v with $y^v_c = 0$ is more than $\frac{1}{2}$ and will not vote for the leader of party Z (the distance between them is at least 1 while it is less than one with s_2), we still have $P^{s_2}_{1\cap 2} = 1$. Hence, we have a profitable deviation, a contradiction. Therefore, we must have $y^{s_1}_c = 0$. ■

Figure 2.C.1 shows an example explaining the intuition of the theoretical model. The different colored lines represent voters preferences, where m_L and$m_R$are positions of party's voters L and R respectively, while m_{sw0} and m_{sw1} are the swing voters positions. The main focus of this example is to elucidate why some political topics polarize more than others. According to the theoretical findings, politicians are expected to polarize along the horizontal axis (cultural topic), taking positions at the extremes of 0 and 1. However, when we consider the vertical axis, we observe that polarization is not conducive to optimal outcomes in elections. Remarkably, any deviation from extreme positions toward the median value on the vertical axis leads to an increase in the number of votes received. This trend applies to both political parties involved. Consequently, it is not possible that any party would position itself strictly at 0 or 1 on this axis. As a result, we can anticipate a relatively smaller disparity in economic stances (and thus opinions) compared to the broader spectrum of positions seen in the cultural domain. By highlighting this disparity, our analysis demonstrates that economic considerations tend to converge to a certain extent, limiting the range of differences in opinions between political parties. On the other hand, the cultural dimension exhibits a wider divergence in positions, indicating a greater scope for varying opinions. This example within our theoretical framework provides valuable insights into the dynamics of political polarization.

Figure 2.C.1: Example



Notes: This figure shows an example useful for explaining the main results of theoretical model.

Chapter 3

Political Campaigning, and Racial Discrimination in Arrests for Drug

3.1 Introduction

Political campaigning can have direct consequences on the behavior of individuals. The recent Capitol Hill attack, during which a mob of Trump supporters attacked the Capitol building in Washington D.C. (New York Times, 2021) is a clear example of how citizens, ignited by harsh political campaigning, can resort to violence. A recent literature in the social sciences has studied how political campaigning can lead to violence against minorities, and found that social media activity of politicians, as well as political rallies or merely winning an election are sufficient to trigger the violent behavior of certain individuals (Müller and Schwarz, 2020; Romarri, 2020; Feinberg, Branton and Martinez-Ebers, 2022; Grosjean, Masera and Yousaf, 2022).

In this paper we study how political campaigning can affect the behavior of law enforcement officers. In particular, we focus on the United States of America (US) during the second Reagan mandate. During these years, Republicans pushed a strong *tough on crime* campaign. This campaign focused on the *War on Drugs* and in particular on fighting crack cocaine, a smokable form of cocaine that started becoming popular in the mid 80's. Presidents Reagan and Bush Sr. played a central role in this campaign and developed a strong presidential rhetoric against drug abuse. Alexander (2011) argues that the *War on Drugs*, is to blame for a change in enforcement behavior at all levels of the American Justice System, leading to large racial inequalities in arrests for possession of illicit substances (Figure 3.2.1).[1] Beckett (1999) and Haney-López (2014) argue that the *War on Drugs* served as a *dog whistle*, a coded racial appeal that carefully manipulated hostility towards non-whites. It is therefore important to answer the following questions: did the presidential rhetoric against drug abuse influence the behavior of law enforcement officers? If the behavior of law enforcement officers did change, did this change in behavior disproportionately affect minorities?

[1]This view is contrasted by Boggess and Bound (1997); Grogger (1998), who attribute the increase in the racial gap in arrests to the rise of crack cocaine and a fall in real wages that hit Blacks particularly hard during the 80's.

We focus on two landmark moments in the history of the US's *War on Drugs*: the introduction of the 1986 and of the 1988 Anti Drug Abuse Acts (ADAA). These two laws marked a punitive turn against the possession of illicit substances. In particular, they both contained severe penalties for possession of crack cocaine. Crucially, however, these two laws were not supposed to affect the vast majority of arrests for possession of illicit substances, as federal laws focus on crimes that involve an inter-state component, such as drug trafficking.[2] For this reason, we consider the 1986 and 1988 Anti Drug Abuse Acts as an example of *dog whistle* politics (Haney-López, 2014): a way for the President to convey a call to action against the stereotypical crack cocaine abuser. Or, in another way, a signal of the President to shift individual efforts of law enforcement agents by *going public* (Kernell, 2006). In this paper, we investigate the link between the presidential rhetoric against drug abuse and arrests for possession of crack cocaine. We provide extensive evidence that more politically competitive counties — counties with similar vote shares for Republicans and Democrats in previous election rounds — were more exposed to the presidential rhetoric against drug abuse — measured by the occurrence of specific war-on-drugs-related keywords in local newspapers —.

We estimate the causal impact of presidential rhetoric against drug abuse on arrests for crack cocaine. Using a difference-in-differences (DD) methodology, we exploit geographic variation in exposure to the presidential rhetoric against drug abuse and time variation in the intensity of the presidential rhetoric against drug abuse, proxied by the enactment of the 1986 and 1988 ADAAs. We estimate separate DD models for arrests for possession of cocaine for Blacks and Whites. Crucially, in our main specification, along with unit and time fixed effects, we also include state by year fixed effects. This approach allows us to control for any state specific policy that was passed either before or after the passage of the 1986 and 1988 Anti Drug Abuse Acts, making the interpretation of our findings consistent with a change in enforcement behavior caused by exposure to the presidential rhetoric and not by state-specific policies. We compare *changes* in arrests for possession of crack cocaine across police agencies in different counties, but in the same year and in the same state. The identifying assumption behind this design is that the trends in arrests for possession of crack cocaine would have been the same for agencies in counties with high and low political competition — conditional on our set of fixed effects and covariates— in the absence of the Republican *tough on crime* electoral campaign.

Our results show that exposure to the presidential rhetoric against drug abuse caused

[2] Bringing drugs from New York to California would be a crime that has an inter-state component and could be dealt with by federal agencies, consuming drugs in New York would not, and would be dealt with by local authorities. Therefore, arrests for possession of illicit substances should be unaffected by the 1986 and 1988 ADAA, as individuals arrested for possession of illicit substances would normally be arrested by local police agencies that apply the laws of the states they are in.

a sharp increase in arrests for possession of crack cocaine for Blacks and had no statistically significant effect for arrests for possession of crack cocaine for Whites. In particular, we find that arrests for possession of cocaine and heroin increase by 6.6% in counties that are more exposed to the presidential rhetoric after the introduction of the 1986 ADAA.[3] Consistent with the arrests being caused by the exposure to the anti-crack cocaine presidential rhetoric, we find no statistically significant impact of political campaigning on arrests for other drugs such as marijuana or synthetic drugs or for other crimes such as prostitution, robbery, driving under the influence or murder — crimes that are also normally associated with an increase in consumption of crack cocaine —. We estimate a triple difference in differences model, whereby we test for differential impact of the presidential rhetoric by race by comparing the impact of the presidential rhetoric against drug abuse on arrests for possession of crack cocaine for Blacks and for Whites. Our results indicate that law enforcement officers arrested 8% more Blacks in counties that were more exposed to the presidential rhetoric against drug abuse.

We construct a novel measure of the intensity of the presidential rhetoric against drug abuse. We collect 11,171 public papers (speeches, statements, and official papers) released by Reagan and Bush from 1984 to 1990. We use the text of these documents as data and let a Latent Dirichlecht Allocation (LDA) algorithm identify the topics that are most often mentioned in this corpus of text. This procedure allows us to identify the topics that characterize the presidential rhetoric and to get an intensity measure for each topic that varies over time. Reassuringly, the unsupervised algorithm clearly defines a topic for the *War on Drugs*. We show that this topic started becoming more relevant immediately after the 1986 Anti Drug Abuse Act and became even more relevant after the 1988 Anti Drug Abuse Act. We complement our DD analysis with a Bartik-type approach, whereby we interact a measure of exposure to the presidential rhetoric with our measure of intensity of the presidential rhetoric against drug abuse — which has the advantage to vary over time, measuring in a more precise way when the presidential rhetoric against drug abuse was stronger —. The results of this exercise are in line with those obtained from the DD analysis.[4]

We show that our results are driven by exposure to the presidential rhetoric against drug abuse. We provide evidence that counties that were more politically competitive were also more exposed to the presidential rhetoric against drug abuse. Previous literature has shown how the media can affect the behavior of law enforcement officers and influence individuals' perceptions and beliefs (DellaVigna and Kaplan, 2007; Snyder Jr and Strömberg, 2010; Mastrorocco and Ornaghi, 2020). We collect articles from 1329

[3] Our data groups arrests for possession of cocaine and heroin in a single category

[4] We obtain similar results when using the raw count of the times the word *drug* has been used in Presidential papers.

local newspaper and count the occurrences of words related to the presidential rhetoric against drug abuse. We find that local newspapers in counties that were politically competitive were more likely to talk about the *War on Drugs*, about crack cocaine, and about classic examples of *dog whistle* politics, like *welfare queen* and *Willie Horton*.[5] Moreover, consistent with increased exposure to Republican campaigning, we also show that municipalities that were in counties that were more exposed to the presidential rhetoric were more likely to have a Republican mayor being elected after the introduction of the 1986 and 1988 ADAAs. We implement a regression discontinuity design at the municipality level and show that having a republican mayor does not increase arrests for crack cocaine for Blacks. We interpret this finding as evidence that our findings are driven by the exposure to the presidential rhetoric against drug abuse and not by a *chain-of-command* effect.

In the spirit of Grosjean, Masera and Yousaf (2022) we test whether Reagan's political rallies caused a racial gap in arrests for possession of crack cocaine. Implementing a triple differences event study, we find that the racial gap in arrests increased by 50 percentage points in cities where rallies were held and during the month in which the rally was held, while we do not find any statistically significant differences in the racial gap both before and after the rallies.

We find that in counties that were more exposed to the presidential rhetoric against drug abuse individuals shift their attitudes toward Blacks. We exploit individual-level survey data from the American National Election Studies (ANES). We find that individuals in counties more exposed to the rhetoric tend to hold more negative attitudes towards Blacks, perceiving them as receiving more than they deserve and needing to try harder to succeed.

We show that our findings are not driven by law enforcement officers who operate in counties with higher racial bias at baseline — proxied by historical indicators of racial bias, such as the presence of enslaved people in 1860, cotton suitability, and the number of lynchings of Black people —. This finding is compatible with the presidential rhetoric being targeted at politically competitive counties, as one of the main correlates of the past presence of slavery is the Republican vote share at the county level. We reconcile these facts with the presidential rhetoric against drug abuse acting as an enabling tool for institutional discrimination. Supporting the view of Alexander (2011), we present evidence that the rhetoric re-directed law enforcement effort towards the prosecution of a minority group, contributing to the systemic discrimination and unequal treatment

[5] *Welfare Queen* is a derogatory term used in the United States to refer to women who allegedly misuse or collect excessive welfare payments through fraud, child endangerment, or manipulation. *Willie Horton* was the name of felon whose case played a crucial role in the debate preceding the 1988 presidential election.

experienced by this community.

This paper contributes to a strand of the literature in economics that examines racial discrimination in law enforcement and in the Criminal Justice System. Knowles, Persico and Todd (2001) show that Black motorists are more likely to be stopped than white motorists, although they find this behavior to be consistent with statistical discrimination. This finding is also consistent with Grogger and Ridgeway (2006), who use stops of motorists at night to test for racial bias in stops, under the assumption that racial profiling of stops is more difficult at night. Antonovics and Knight (2009), on the other hand, argue against the results obtained in Knowles, Persico and Todd (2001) and by extending their model they find evidence for preference-based discrimination when the race of the officer differs from the race of the driver, moderate evidence for racial bias in stop and searches is also found in Anwar and Fang (2006). Related to our paper (Grosjean, Masera and Yousaf, 2022) find that Trump rallies increase racial bias in car stops. Evidence for racial bias in criminal trials is less ambiguous than evidence on racial bias in stops. Anwar, Bayer and Hjalmarsson (2012) finds that white jury pools are more likely to punish black defendants, Rehavi and Starr (2014) finds that Blacks are more likely to be charged for crimes with a mandatory minimum sentence, leading to higher conviction rates. Similar findings are obtained by Arnold, Dobbie and Yang (2018) when considering bail decisions, by West (2018) when considering police investigations, by Goncalves and Mello (2021) when considering discount on speeding tickets and by Tuttle (2019) when considering charges for drug offenses and by Hoekstra and Sloan (2020) when considering police use of force. We expand upon this literature and show that political campaigning strongly contributed to the large racial gap in arrests for possession of illicit substances that characterized the US throughout the last century.

This paper also contributes to a strand of literature in other social sciences that explicitly considers political competition as a driver of tougher law enforcement. Jacobs and Helms (1996) test if political competition for votes during presidential campaigns is correlated to a larger number of arrests, they find that the number of arrests increases in years immediately following elections.[6] Stucky, Heimer and Lang (2007) find that state-level spending for corrections is positively correlated with strengths of the Republican party and finds only limited evidence for a reduction in spending for corrections when political competition is tighter. However, Stucky, Heimer and Lang (2005) find that imprisonment rates increase in states where Republicans control the state legislature and political competition is tighter. This strand of the literature only analyzes correlations between political variables and criminal justice outcomes. We contribute to this literature in two ways: firstly, we employ a research design that can estimate

[6]Similar results are obtained in Caldeira (1983) for correctional spending

the causal impact of political campaigning on the racial gap in arrests. Secondly, we explicitly consider how political campaigning affects the racial gap in arrest, a point that has not yet been addressed empirically in the literature.

3.2 Institutional Context

3.2.1 The War on Drugs

The *War on Drugs* is a global campaign led by the US federal government to combat the illegal drug trade and drug abuse in the US. The term *War on Drugs* was popularized after a press conference by Richard Nixon in 1971. The former US president called for a strong offensive against drug abuse, which was described as public enemy number one in the US. The *War on Drugs* has been at the center of the political debate since then, gaining considerable attention from the media.

Young black males have been the biggest victims of the huge media attention that the *War on Drugs* gained. Blacks were overtly represented in media news about drug crimes. By 1986 terms like *crack babies* started making the headlines of the main news outlets, depicting children of drug abusers as a biological underclass of children who would require state support for the rest of their lives (Ahrens, 2009).

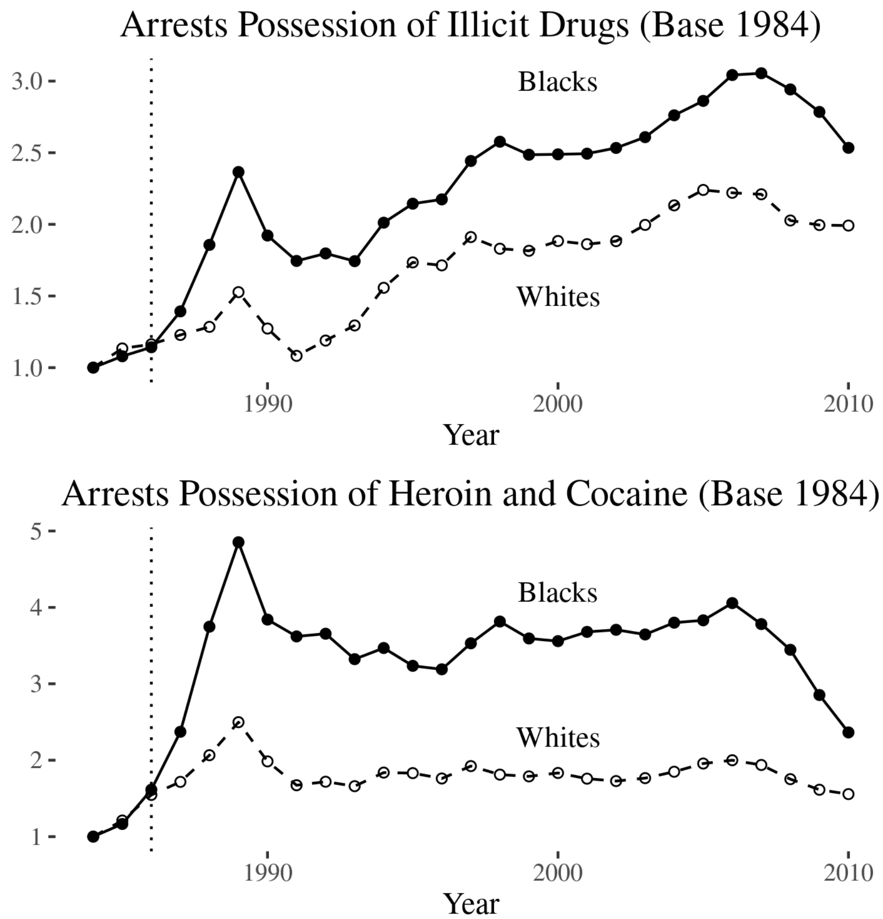
The disproportionate impact of the *War on Drugs* on Blacks is rooted in the strong fear that Americans had about law and order collapsing due to a strong rise in crimes committed by Blacks. As Beckett (1999) and Moriearty and Carson (2012) show, by 1968 the overwhelming majority of Americans believed that crime was on the rise and that "Negroes who start riots" Beckett (1999) were the cause.

Arrests for possession of illicit substances for Blacks almost doubled from 1986 to 1988. Arrests for possession of heroin and cocaine – the category that includes crack cocaine – more than tripled from 1986 to 1988. The same did not happen for Whites, who experienced an increase in arrests for possession of illicit substances, but to a much lesser extent. This racial disparity in the increase in arrests for possession of illicit substances continued for decades. We illustrate this point in Figure 3.2.1, where we report an index for arrests for possession of illicit substances for Blacks and Whites from 1984 to 2010.

3.2.2 Reagan and the punitive approach to the *War on Drugs*

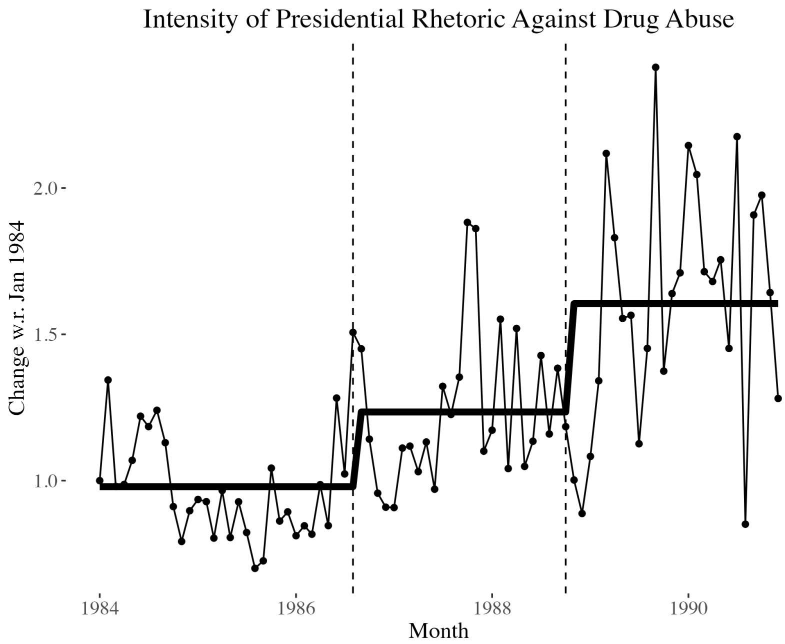
In September 1986 Ronald Reagan and his wife Nancy addressed the Nation on the Campaign against Drug Abuse, calling for a national crusade against drugs. President Reagan proudly announced that under his administration spending for drug law en-

Figure 3.2.1: Trends in Arrests for Possession of Illicit Substances



Notes: This Figure plots the number of arrests for possession of illicit drugs (top panel) and for possession of cocaine or heroin (bottom panel) in the UCR data. Arrests are indexed with respect to the number of crimes committed in 1984. The dashed vertical line indicates 1986, the year during which the first Anti Drug Abuse Act was passed.

Figure 3.2.2: The Evolution of the Relevance of Drugs



Notes: This figure plot the change in intensity in the drug topic in the US President public papers (Reagan and Bush) from 1984 to 1990. The solid bold black lines represent the averages before the 1986 ADAA and after the 1986 ADAA and the 1988 ADAA.

forcement tripled since 1981, increasing seizures of illegal drugs and causing shortages of marijuana. Nancy Reagan launched the *Just Say No* campaign, stressing the importance of individual responsibility in fighting the *War on Drugs*. During the speech, President Reagan announced a series of measures aiming at creating a "Drug Free America" (Reagan, 1986).

After September 1986, the *War on Drugs* became a central topic of the Republican political platform. Figure 3.2.2 shows the importance of the *War on Drugs* topic in public papers (statements, speeches, and official papers) by President Ronald Reagan and George H. W. Bush from 1984 to 1990.[7] The pattern displayed in Figure 3.2.2 is clear, and shows how after September 1986 the *War on Drugs* played a central role in the republican policy platform. The importance of the *War on Drugs* topic further increased after the Presidential Election of 1988 and the passage of the 1988 Anti Drug Abuse Act.

During his presidency, Ronald Reagan pushed for a tougher and more punitive approach to illicit drug trade and illicit drug use. In 1984, the Reagan administration passed the Comprehensive Crime Control act, which expanded penalties towards possession of

[7]We obtain this measure through a topic modeling analysis conducted on all public papers by Reagan and Bush sr. between 1984 and 1990. We give a detailed description of how we obtain this measure in the data section of the paper.

cannabis and established a federal system of mandatory minimum sentences. The 1984 Comprehensive Crime Control Act was followed in September 1986 by the Anti Drug Abuse Act, which substantially increased the number of drug offenses with mandatory minimum sentencing. Moreover, the 1986 Anti Drug Abuse Act introduced the 100:1 weight ratio between crack cocaine and powder cocaine. This act mandated a minimum sentence of five years without parole for possession of 5 grams of crack cocaine while it mandated the same for possession of 500 grams of powder cocaine. At the end of Reagan's second term, in 1988, Congress passed an additional Anti Drug Abuse Act, that toughened the measures contained in the 1986 Act, especially for crack cocaine, and restored the use of the death penalty at the federal level.

The Reagan administration strongly pushed for tougher penalties for illicit drugs users and dealers. The majority of drug crimes, however, are normally prosecuted by local and state authorities. If a drug crime does not involve any crossing of state borders, federal policies do not play a role in determining how that crime should be prosecuted. For this reason we consider the 1986 and 1988 Anti Drug Abuse Acts as a way for the President to steer the actions of state governments and law enforcement authorities towards a harder stance with respect to possession of illicit drugs, especially crack cocaine. In particular, in Reagan's — and later on in Bush's Sr. — presidential rhetoric this attention to crack cocaine has been considered as a *dog whistle* to focus the efforts of law enforcement officers towards the prosecution of Black Americans using crack cocaine (Yates and Whitford, 2009; Haney-López, 2014). A number of governors responded to the President's call to action against drug abuse and passed laws that were using the 1986 and 1988 Anti Drug Abuse Acts as a blueprint for tougher drug laws (Malone, 2018; Britton, 2021). Moreover, the 1986 Anti Drug Abuse Act allowed for direct transfers from the federal government to states and police agencies in the form of grants for state and local law enforcement, administered by the Office of Justice Assistance (Hogan and Walke, 1987).

3.2.3 *Tough on Crime* policy and the 1988 election

Tough on Crime policies were at the center of the 1988 presidential Election, won by the Republican Candidate George H.W. Bush. In May 1988 the Democratic presidential candidate and Governor of the State of Massachusetts, Michael Dukakis, was leading the polls for the upcoming presidential election with a margin of 16pp. Since June 1988, the Republican campaign focused on the case of Willie Horton. A black convicted felon who — while serving a life sentence for murder — was the beneficiary of a Massachusetts weekend furlough program strongly endorsed by Dukakis. Horton did not return from his furlough, and twice raped a woman after pistol-whipping, knifing, binding, and gagging her fiancé. The case happened in 1987, while Dukakis was still Governor of

Massachusetts, but did not gain much attention until it was used by Republicans – starting from June 1988 – to earn the trust of voters with strong preferences for *tough on crime* policies. Bush's campaign manager at the time, Lee Atwater, said: "By the time we're finished, they're going to wonder whether Willie Horton is Dukakis's running mate" (Runkel, 1989).

3.3 Data and Descriptive Evidence

We construct a panel at the police agency year-month level. In total, we combine data from different sources which we describe in more detail in the following subsections. Summary statistics for the main variables of interest can be found in the Appendix (Table 3.A.1).

Data about Crime The Uniform Crime Report dataset (UCR) reports monthly arrests at the police agency level from 1978. We use the data provided by Kaplan (2020). Participation in the program is not mandatory, and police agencies often do not report during some months. This feature of the dataset makes it problematic to use information about all police agencies included in the dataset, in particular if there would be some unobserved selection mechanism in reporting to the UCR program, any causal analysis could be biased by selection into reporting. We mitigate this issue by restricting our sample to agencies that continuously report in all months from January 1984 to December 1990 – i.e. we follow the same police agencies over time – .[8]

All crime variables report the number of arrests for a given police agency in a given month by race. The main outcome of interest is arrests for possession of heroin and cocaine, which includes arrests for crack cocaine. Furthermore, as a robustness check, we use arrests for driving under the influence (DUI), murder, prostitution and robbery, as well as arrests for possession of other substances. We transform these variables using the inverse hyperbolic sine transformation. This transformation is similar to the natural logarithm transformation, but allows to account for the prevalence of zeros, while still allowing to interpret estimates as elasticities (Bellemare and Wichman (2020)). This transformation is particularly convenient in this setting, as oftentimes there are zero crimes registered in a particular police agency in a given month.[9] Our final dataset consists of a panel dataset balanced at the police agency level where we observe 1383

[8] We show in the appendix that our results are robust to alternative ways of cleaning the data, following Evans and Owens (2007); Chalfin and McCrary (2018); Mello (2019).

[9] For empirical applications of the inverse hyperbolic sign transformation see Bahar and Rapoport (2018),Card, DellaVigna, Funk and Iriberri (2020) and Facchetti (2020). In an alternative specification, in the robustness section of the paper, we also use the number of arrests instead of the IHS and poisson pseudo maximum likelihood (Silva and Tenreyro, 2006) instead of OLS.

different police agencies in 662 counties in 40 US states from January 1984 to December 1990.

We choose to use the police agency as our unit of observation, as we have differential coverage across counties and states in our sample (i.e. for some counties and for some states there is only a fraction of the police agencies continuously reporting to the program). Using the police agency as the unit of observation in our dataset allows us to exploit the information about the population that every agency is supposed to cover and to obtain a rough measure of the coverage by county. In the robustness checks section, we estimate our main specifications on a sub-sample of our main dataset, where we only include counties for which the police agencies in our dataset are supposed to cover at least 80% of the population in that county.[10]

Data on Electoral Outcomes We obtain data on county-level electoral outcomes for elections of presidents and governors from the General Election Data for the United States. We use data on the 1984 presidential elections to generate our measure of electoral competition at the county level as the absolute difference between the vote share for Republicans and Democrats at the county level:

$$\text{Political Competition}_{c,1984} = 1 - |\text{Rep Share}_{c,1984} - \text{Dem Share}_{c,1984}|$$

where subscript c indicates any given county, and $\text{Rep Share}_{c,1984}$ and $\text{Dem Share}_{c,1984}$ indicate the vote shares of Republicans and Democrats in county c for the 1984 presidential election.[11] We choose to use the vote shares for the presidential elections in 1984 as they represent the closest election to the 1988 presidential election. Crucially, we measure political competition before the 1986 ADAA, to avoid the potential direct impact of the 1986 ADAA on political competition. In the robustness section of the paper we show that our results are largely unaffected by using a measure of political competition that is obtained from presidential elections in alternative years, or from the average results of elections in the previous 12 years.

We define a county to be treated if its value of $\text{Political Competition}_{c,1984}$ is greater than the median value (0.74). According to our definition a county is defined as treated if the difference in vote shares between Republicans and Democrats in 1984 was less

[10] On this same sample we estimate our main specifications using the crime rate as our dependent variable. As we need race-specific crime rate and we do not observe the racial composition of the population that a given police agency is supposed to patrol, we only estimate our model using crime rates as the dependent variable when we can observe a reasonably high share of the county's population and by using the 1980 census to calculate race-specific crime rates. We show these results in the robustness section.

[11] In the section of the paper dedicated to robustness checks, we estimate our model using previous election years and an average of elections between 1972 and 1984

Figure 3.3.1: Monthly Arrests for Possession of Heroin and Cocaine

Notes: This Figure plots the total number of monthly arrests for possession of heroin or cocaine by Blacks in our treated and control counties. The two solid lines indicate the passage of the 1986 and 1988 Anti Drug Abuse Acts

than 26%. Figure 3.B.1, in the appendix, shows a map of treated and control counties. Figure 3.3.1 shows the sum of arrests for possession of heroin and cocaine for Blacks in treated and control counties. It is clear how arrests for possession of heroin and cocaine started increasing immediately after the 1986 ADAA in both the treatment and the control group. Figure 3.B.2, in the appendix, shows an histogram of our measure of political competition.

Data on presidential rethoric - Public papers by the President We construct a novel dataset containing all public papers by President Reagan and by President Bush from 1984 to 1990. We obtain this information from the Ronald Reagan Presidential Library and from the George H.W. Bush Presidential Library.[12] This dataset contains the text of all the public speeches, statements and papers from both libraries, as well as the date of the speeches.

We construct a measure of the importance of the *War on Drugs* in the presidential rhetoric. We first pre-process the text of all public papers by Reagan and Bush following Gentzkow, Kelly and Taddy (2019). We normalize the text by removing all the “stopwords", punctuation, numbers and we apply the ‘stemmatization" of the words using Porter, Boulton and Macfarlane (2002) procedure. We then implement a Latent Dirichlet Allocation (LDA) model (Blei, Ng and Jordan, 2003; Martin and McCrain, 2019). This unsupervised technique characterizes what the most discussed

[12]https://www.reaganlibrary.gov and https://bush41library.tamu.edu

topics among all public papers by the president are and what are the words that most often recur within each topic. In Figure 3.B.3, in the appendix, we report the result of our LDA topic modeling showing the 10 bigrams (combination of two words) with the highest weights for each topic. We identify *topic 10* as the one characterizing the presidential rhetoric against drug abuse. This topic is characterized by the bigrams *law enforcement, supreme court, attorney general, drug abuse* and *illegal drug*. We use the importance of this topic — i.e. its weight among all topics identified in presidential papers — as our measure for the intensity of the presidential rhetoric against drug abuse.

In Figure 3.2.2 we plot the evolution of the relevance of the intensity of the presidential rhetoric against drug abuse over time, along with the average intensity before and after the 1986 and 1988 ADAA (the bold solid line).[13] The time series shows a clear increase in how important the topic of drug abuse is after both the 1986 ADAA and the 1988 ADAA, immediately after the 1988 presidential elections.

Data on the content of newspapers We scrape the content of 1329 local newspapers on newspapers.com. We count the number of times that a local newspaper in a given county mentions keywords that are related to the *War on Drugs*. Unfortunately, we are not able to observe the universe of local newspapers and to match that to the counties that we observe in our main dataset. Because of these constraints we obtain data about the occurrence of words related to the *War on Drugs* for 1117 cities in 377 counties in 45 states. We focus on different *War on Drugs* terms used by Reagan during his presidency: *"crack cocaine"*, *"crack babies"*, *"war on drugs"*, *"welfare queen"*, *"just say no"*, *"Willie Horton"*. Some of these terms directly refer to illicit drugs, while some others (such as *"Willie Horton"* and *"welfare queen"*) are words that have been used during the presidential campaign (and before that) and are commonly considered as ways to depict Blacks as either criminal or welfare state abusers. We use this data to measure the exposure to the presidential rhetoric against drug abuse.

Reagan Visits We collect the domestic visits of Ronald Reagan from 1981 to 1989 from the Ronald Reagan Presidential Library and Museum. We then match the places visited by the US President with the police agencies over time. We end up with 258 visits undertook by Ronald Reagan during his presidency. We can observe the date, the place (and the state) and the motivation (event) of the visit. Of these visits, just 107 were motivated as political rallies. We use this data to test if places that were visited by Ronald Reagan experienced an increase in arrests for possession of crack

[13] In Figure 3.B.4, in the appendix, we plot the number of times that the word *drug* has been used in Reagan and Bush's public papers. In Figure 3.B.5, in the appendix, we compare the importance of the topic *Economy* with the importance of the presidential rhetoric against drug abuse.

cocaine after his visit. As we are interested in political rallies that happened at the peak of the presidential rhetoric against drug abuse we restrict our analysis to political rallies after the implementation of 1986's ADAA (during the 1988 presidential electoral campaign). This leaves us with 14 political rallies by President Reagan between 1986 and 1988 in places where we also have data about crime outcomes.

Data on crack cocaine prevalence We obtain the crack prevalence index from Fryer Jr, Heaton, Levitt and Murphy (2013). In particular, we use annual crack prevalence indices at the state level for all US states. We are interested in the state level crack prevalence index in 1985, as we use it as a non-parametric control for crack prevalence before the passage of the 1986 Anti Drug Abuse Act.

Data on municipality elections We obtain data about the results of 895 mayoral elections in the US between 1984 and 1990 from de Benedictis-Kessner (2018). We use this data to test whether in counties that were more exposed to the republican presidential campaign, Republicans had an electoral advantage in local elections. Moreover, we implement a regression discontinuity design to test if the election of a Republican Mayor influenced the behavior of law enforcement officers.

Data on racial resentment We collect data on the presence of enslaved people in 1860, cotton suitability and the number of lynchings of Black people from (Acharya, Blackwell and Sen, 2016). We use this data as a proxy for racial resentment. We then test whether counties that have higher racial resentment experienced a higher increase in the racial gap in arrests for possession of crack cocaine.

Socio Economic Characteristics of Counties We use the 1980 census data to retrieve information at the county level about counties' socio economic characteristics. In particular, we gather information at the county level for population, the share of population under 10, between 10 and 18, and over 18, the share of female, the share of black and the percent below poverty level. We use this data to analyze whether counties that are included in our sample – for which we observe at least one police agency continuously reporting between 1984 and 1990 – do systematically differ from an average county in the US. Moreover we use this data to test whether counties that we consider as treated systematically differ from control counties in our sample.

Table 3.A.2 shows the mean, the standard error and the normalized difference for counties that are in our sample and counties that are not. The main differences between sampled and not sampled counties, those for which the normalized difference is higher that the threshold of 0.25 suggested by Imbens and Rubin (2015) are that sampled countries have a higher population and a lower share of the population below the

poverty level (roughly 4% less). These differences do not affect the internal validity of our study but need to be taken into account when interpreting our estimates, as they are only going to be generalizable to highly populous and slightly richer counties. Crucially, counties that are included in our sample do not display significant differences in the average level of political competition.

Table 3.A.3 shows the mean, the standard error and the normalized difference for counties that are in our treatment group and counties that are in our control group. As political competition is not randomly assigned to counties, we find that treated counties are systematically different from control counties. Our treated counties have a significantly higher proportion of Blacks, female and individuals below the poverty line. In our identification strategy we correct for this imbalance in two ways. Firstly we include a battery of fixed effects and rely on a parallel trend assumption to identify a causal effect — the standard difference in differences approach —. Secondly, we control for the impact of differences in baseline characteristics by adding an interaction between baseline characteristics and the start of our treatment.

3.4 Empirical Strategy

The goal of this paper is to estimate if political campaigning can influence the behavior of law enforcement officers. In particular, we focus on the presidential rhetoric against drug abuse that characterized the Republican agenda during the second Reagan mandate and the 1988 presidential campaign. We concentrate on arrests for possession of crack cocaine, as the presidential rhetoric against drug abuse was heavily focused on this type of crime.

Estimating and isolating the causal effect of exposure to the presidential rhetoric against drug abuse on law enforcement behavior presents several challenges. Firstly, the presidential rhetoric against drug abuse can affect law enforcement officer's behavior both directly – by making the issue of drug abuse more salient to them – or indirectly – as state governors might implement tougher laws against drug abuse – . As we are dealing with police officers from local police agencies, their law enforcement behavior should be driven by state laws, a feature that poses a problem in isolating only the direct influence of the presidential rhetoric against drug abuse on law enforcement behavior. Secondly, it is challenging to find places that are exposed to the presidential rhetoric against drug abuse and places that are not. Moreover, even with geographical variation in the exposure to the presidential rhetoric against drug abuse, this variation can co-vary with several characteristics that are also correlated with law enforcement behavior.

To estimate the impact of the presidential rhetoric against drug abuse on arrests for crack cocaine, one would like to randomly allow some places to be exposed to the presidential rhetoric against drug abuse – the *treated* units –and some places to be not exposed to it – the *control* units –. In this case by simply comparing the arrests for crack cocaine in control and treated units, one would be able to obtain a causal estimate of the effect of the exposure to the presidential rhetoric against drug abuse on arrests for crack cocaine. Moreover, by comparing outcomes for Blacks and Whites in treated units with outcomes for Blacks and Whites in the control units, one would be able to state whether the presidential rhetoric against drug abuse caused a racial gap in arrests for crack cocaine. This approach would guarantee that the presidential rhetoric against drug abuse is affecting some places but not others, and by picking these places randomly, would also allow us to disentangle the direct effect of the presidential rhetoric against drug abuse from the indirect effect. This is because, by design, states with tougher anti-drug laws will appear both among the treated and the control units.

We approximate this ideal setting through two complementary identification strategies: a difference-in-differences approach and a Bartik-type approach. Both approaches rely on the assumption that more politically competitive counties are more exposed to the presidential rhetoric against drug abuse, for which we provide extensive evidence in the mechanism section of the paper. The underlying logic of this approach is that officers who are operating in more politically competitive counties are more exposed to political campaigning and to the presidential rhetoric against drug abuse. In both identification strategies we measure political competition at the county level. This approach will allow us to include – on top of the traditional battery of unit and time fixed effects – state by year fixed effects, that will absorb state-specific policies. This approach will allow us to separate the direct and indirect effect of the presidential rhetoric against drug abuse, by comparing counties that face the same state laws but have different levels of the exposure to the presidential rhetoric against drug abuse.

3.4.1 The effect of political competition on arrests for crack cocaine

Difference in Differences We identify the effect of the presidential rhetoric against drug abuse on arrests for crack cocaine using a difference in differences research design. We exploit geographical variation in political competition and time variation in the intensity of the presidential rhetoric. We consider counties to have a high level of political competition if the absolute difference in vote shares for Republicans and Democrats was less than the median absolute difference in vote shares between Republicans and Democrats in 1984. We assume that counties that were more politically competitive were more exposed to the presidential rhetoric against drug abuse and provide extensive evidence in support of this assumption in the mechanism section of the paper.

We estimate separate difference in differences model for Blacks and for Whites, whereby we compare the *changes* in arrests for possession of cocaine in counties with high and low levels of political competition before and after the passage of the 1986 and the 1988 Anti Drug Abuse Acts, which we consider as a way for the President to re-direct law enforcement officers' effort. We do this by estimating the following model by OLS:

$$y_{pt} = \beta \text{Pol. Comp.}_c \times \text{Post}_t + \delta_p + \delta_t + \delta_{sy} + \mathbf{X}_c \times \text{Post}_t + \text{population}_{pt} + \epsilon_{pt} \quad (3.1)$$

The outcome is the inverse hyperbolic sine transformation for arrests for possession of cocaine or heroin for Blacks or Whites in police agency p in month t (in county c). We regress the outcome on our measure of pre-1986 political competition at the county level and a post dummy variable, which takes value one after the passage of the 1986 Anti Drug Abuse Act. We control for police agency (δ_p) and month $\times$ year (δ_t) fixed effects. The fixed effects absorb any feature that does not vary over time across police agencies and account in a non-parametric way for national time trends in crime rates, consumption of crack cocaine and any national trend in the propensity to record crimes. Moreover, in our main specification we control for state by year fixed effects (δ_{sy}) that absorb any state specific shock in a certain year, such as state specific policies. Finally, we control non-parametrically for baseline difference in covariates $\mathbf{X}_c$ by interacting these covariates with a Post dummy. These covariates include: a state level indicator of the prevalence of crack cocaine in 1985 at the state level from Fryer Jr et al. (2013), the percentage of Blacks, the percentage of individuals below the poverty line, the percentage of female, the percentages of population over 18 and under 10, as well as baseline population, all measured at the county level according to the 1980 census. These controls account for the differential effect of anything that happened after 1986 and that was related to the controls. Most importantly, they ensure that our effects are not driven by baseline differences in the percentage of Blacks. The identifying assumption behind this design is that the trends in arrests for possession of crack cocaine for Blacks and Whites would have been the same for agencies in counties with high and low political competition —conditional on our set of fixed effects and covariates— in absence of the 1986 and the 1988 Anti Drug Abuse Acts.

We also estimate dynamic treatment effects through a flexible difference-in-difference model whereby the post-treatment dummy is replaced by month dummies δ_t when we estimate the treatment effect,

$$y_{pt} = \sum_t^T \beta_t \text{Pol. Comp.}_c + \delta_p + \delta_t + \delta_{sy} + \mathbf{X}_c \times \text{Post}_t + \text{population}_{pt} + \epsilon_{pt} \quad (3.2)$$

In both equations, the error term summarizes all the time-varying determinants of arrest for possession of illicit drugs that are not captured by the regressors. To account for serial correlation in the error terms within a given county —the level at which treatment is assigned—, we cluster the standard errors at the county-level.

Triple Differences We estimate a triple differences model where we compare arrests for possession of cocaine or heroin for Blacks in counties with high versus low exposure to the presidential rhetoric to arrests for possession of cocaine or heroin for Whites in counties with high versus low exposure to the presidential rhetoric. This approach has two main advantages. Firstly, it allows us to control for any common shock that affects both Blacks and Whites across counties that might be correlated with exposure to the presidential rhetoric, as well as for the heterogeneous effect that exposure to the presidential rhetoric can have depending on unobserved characteristics of counties, but that does not vary between Blacks and Whites. Secondly, it allows us to get an estimate of the racial gap in the effect of exposure to the presidential rhetoric on arrests for possession of crack cocaine. In particular, estimating a triple differences model amounts to estimate the difference between two difference in differences models — in this case the difference in differences model for Whites and the difference in differences model for Blacks— (Olden and Møen, 2020). More formally, we want to estimate $\xi \equiv \beta_{\text{Blacks}} - \beta_{\text{Whites}}$, where β_{Blacks} and β_{Whites} represent the effect of political competition on arrests for Blacks and Whites and, by definition ξ represents the racial gap in the effect of political competition. To estimate the triple differences model we include outcomes for Blacks and Whites in the same dataset and add an additional dummy variable R that takes value one for outcomes for Blacks. We then interact the dummy variable R with all the independent variables in equation 3.1 in a static triple differences estimation. We then estimate the following:

$$\begin{aligned} y_{ptr} =& \xi \text{Pol. Comp.}_c \times \text{Post}_t \times R + \gamma \text{Pol. Comp.}_c \times \text{Post}_t + \\ & + \delta_p \times R + \delta_t \times R + \delta_p + \delta_t + \delta_{sy} \times R + \delta_{sy} + \mathbf{X}_c \times \text{Post}_t \times R + \mathbf{X}_c \times \text{Post}_t + \\ & + \text{population}_{pt} + \text{population}_{pt} \times R + \epsilon_{ptr} \end{aligned} \tag{3.3}$$

Where y_{ptr} is the inverse hyperbolic sine transformation of the number of arrests for possession of cocaine or heroin in policy agency p in month t and for race r. The right-hand side of the equation is the same as the right-hand side of equation (3.1) where every variable is interacted with the race dummy R, crucially this allows us to separately control for differential trends for crack cocaine consumption across races ($\delta_t \times R$). The coefficient of interest ξ represents the racial gap in the effect of the presidential rhetoric against drug abuse, proxied political competition. The stochastic error term ϵ_{ptr} is again clustered at the county level, to allow for serial correlation of the error term within a given county.

Bartik-type approach We validate our findings using an alternative identification strategy that exploits our novel measure of the intensity of the presidential rhetoric against drug abuse. We estimate a fixed effect panel regression that is similar to a reduced form Bartik-type approach (Bartik, 1991). We use the interaction of a continuous version of our measure of political competition, which varies at the county level, and our monthly measure of the intensity of the presidential rhetoric against drug abuse.[14]. This empirical setup creates variation by month and county, that we exploit using the following regression model:

$$\begin{aligned} y_{pt} = &\psi \text{Pol. Comp.}_c \times \text{presidential rhetoric}_t + \delta_p + \delta_t + \delta_{sy} + \\ &+ \mathbf{X}_c \times \text{presidential rhetoric}_t + \text{population}_{pt} + \epsilon_{pt}. \end{aligned} \tag{3.4}$$

This framework allows us to test whether when the president focuses more on the *War on Drugs* topic, counties that are more exposed to the presidential rhetoric experience more arrests for crack cocaine. This approach does not suffer from reverse causality as arrests for crack cocaine in one county are likely to not affect the way in which the President talks about the *War on Drugs* in the whole country. Moreover our full set of fixed effects controls for unobserved heterogeneity across police agencies, as well as shocks that affect all police agencies, such as changes in the nationwide propensity to consume crack-cocaine for Blacks. Furthermore, our set of controls $\mathbf{X}_c$ account for the effect that the presidential rhetoric against drug abuse can have on arrests due to baseline differences in, for example, the percentage of Blacks or the percentage of individuals below the poverty level in a given county.

The main concern with estimating Equation 3.4 is that political competition — our measure of exposure to the presidential rhetoric — may be correlated with other county characteristics that could explain differences in how arrests for possession of crack cocaine co-vary with the intensity of the presidential rhetoric about the *War on Drugs*. In that case our coefficient of interest ψ would not be solely capturing the effect of political competition. We address this issue by explicitly controlling for the factors that are correlated with political competition — our $\mathbf{X}_c$ — and interacting them with the intensity of the presidential rhetoric against drug abuse.

We estimate a triple difference version of Equation 3.4 where we also include arrests for possession of crack cocaine for Whites. This exercise will alleviate the concern that some unobserved county characteristic might co-vary with the presidential rhetoric

[14] To make the interpretation of our coefficient easier we multiple both measures by 100.

about the *War on Drugs* and be driving our results. This is because the county characteristics that co-vary with the presidential rhetoric against drug abuse should have a differential effect for Blacks and Whites to bias our estimates, but should not be captured by our control for baseline differences in the share of Blacks the county level.

3.5 Results

3.5.1 Difference-in-Differences

Table 3.5.1 shows estimates of Equation 3.1 across different model specifications. In the top panel the outcome is the inverse hyperbolic sine transformation of the number of monthly arrests for heroin and cocaine at the police agency level for Blacks, the second panel reports estimates for the same outcome for Whites. The number of observations is given by the number of police agencies (1383) multiplied by the number of months in the data (84). Columns (1) to (4) report different model specifications.[15]

Estimates of the effect of political campaigning on arrests for Blacks are always positive and show little variation through different model specifications. According to our main specification in Column (4), police agencies in counties that were more exposed to political campaigning — as proxied by political competition in 1984 — experienced a 6.7% increase in arrests for possession of cocaine or heroin after the enactment of the 1986 Anti Drug Abuse Act. On the other hand, we find no effect on the arrests for possession of cocaine or heroin for Whites.

Figure 3.5.1, Panel A reports dynamic treatment effect estimates for the effect of the presidential rhetoric against drug abuse on arrests for possession of illicit drugs for Blacks estimated through Equation 3.2. Estimates before the passage of the 1986 Anti Drug Abuse Act are close to zero and are never statistically significant at the 5% level, a feature that provides evidence in favor of the parallel trend assumption. Estimates start increasing after the passage of the 1986 Anti Drug Abuse Act, and peak right after the passage of the 1988 Anti Drug Abuse Act and the 1988 presidential elections and remain relatively stable after that.

Triple Differences Results Results from the previous section show that political campaigning had an effect on arrests for possession of illicit drugs for Blacks, but show no statistically significant effect for Whites. We provide evidence for a racial gap in the effect of political campaigning on arrests with a triple differences model.Table 3.A.4, in appendix, shows results of a triple differences model estimated according to Equa-

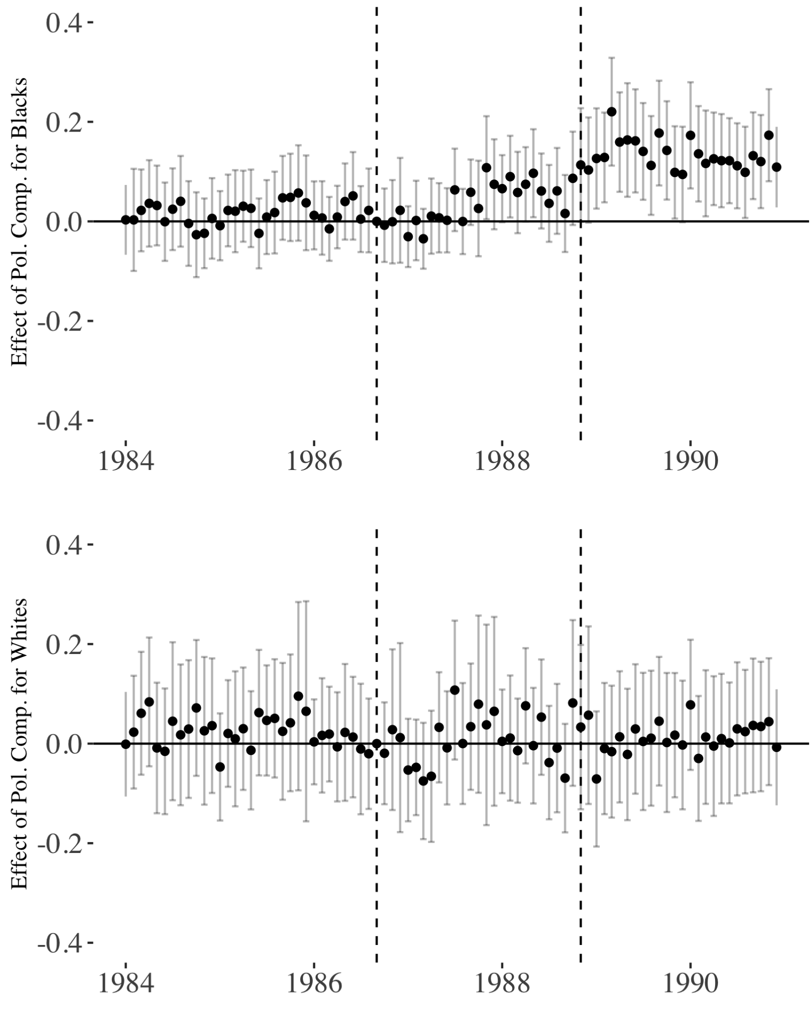
[15] Table 3.A.5, in the appendix, shows the results of our main specifications when we clean the data following Evans and Owens (2007); Chalfin and McCrary (2018); Mello (2019).

Table 3.5.1: Effect of political competition on arrests for possession of cocaine or heroin - DiD

	Dependent variable:			
	Arrests for possession of cocaine or heroin for Blacks			
	(1)	(2)	(3)	(4)
Pol. Comp. X Post	0.0663**	0.0990***	0.0981***	0.0662**
	(0.0330)	(0.0310)	(0.0320)	(0.0317)
	Arrests for possession of cocaine or heroin for Whites			
Pol. Comp. X Post	0.0258	-0.0124	-0.0159	-0.0139
	(0.0496)	(0.0317)	(0.0322)	(0.0309)
Agency FE	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes
State Time Trends FE	No	Yes	No	No
State x Year FE	No	No	Yes	Yes
Controls	No	No	No	Yes
Mean Outcome Blacks	0.3386	0.3386	0.3386	0.3386
Mean Outcome Whites	0.7058	0.7058	0.7058	0.7058
Observations	116,172	116,172	116,172	116,172

Notes: This table shows estimates of Equation 3.1 for arrests for possession of cocaine or heroin for Blacks (top panel) and Whites (bottom panel). The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed. Different columns report different specifications of Equation 3.1. Column 1 reports a specification with police agency and month by year fixed effects. In column 2 we add state specific linear time trends. In Column 3 we control for state by year fixed effects and in Column 4 we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Figure 3.5.1: Dynamic Treatment Effect on Arrests for Blacks and Whites



Notes: This graph shows dynamic treatment effect estimates of the effect of political competition on arrests for possession of heroin and cocaine for Blacks (Panel A) and for Whites (Panel B). The dashed black vertical lines indicate the enactment of the 1968 Anti Drug Abuse Act and the 1988 Anti Drug Abuse Act (which coincided with the 1988 elections). The gray lines show 95% confidence intervals for standard errors clustered at the county level.

tion 3.3. Estimates are similar and stable after accounting for state specific dynamics either through state specific linear trends, column (2) or through state by year fixed effects, as in column (4). These estimates show that political competition exacerbated the racial gap in arrests. We estimate the racial gap in the effect of political competition on arrests for possession of cocaine or heroin between Blacks and White to be of 8% according to our main specification (column 4).

3.5.2 Bartik-type Approach

Table 3.5.2 shows estimates of the interaction term in equation Equation 3.4. Estimates for Blacks are always positive and statistically significant. Estimates for Whites are negative after we start controlling for state specific dynamics and are never statistically significant.[16] Our estimates show that, holding the intensity of the presidential rhetoric against drug abuse constant, a 1% increase in political competition causes a 0.07% to 0.1% increase in arrests for possession of heroin and cocaine for Blacks. These estimates are extremely similar in magnitude to those obtained with our DD estimation strategy. Table 3.A.7, in the appendix, shows estimates of a triple differences version of Equation 3.4. These results confirm again that our findings are driven by a racial gap in arrests for possession of heroin and cocaine for Blacks.

3.6 Mechanism

We provide evidence that the mechanism driving our results is the exposure to the presidential rhetoric against drug abuse. We provide evidence that local newspapers in politically competitive counties mention more words related to the presidential rhetoric against drug abuse more often, validating the use of political competition in 1984 as a good proxy for exposure to political campaigning. We provide evidence that places that have been visited by Reagan for a rally after 1986 (during the 1988 presidential electoral campaign) experienced a racial gap in arrests for crack cocaine during the month of the rally. We show that —- consistently with higher exposure to electoral campaigning — municipalities that were located in more competitive counties, have a higher chance of electing a republican mayor after the presidential rhetoric against drug abuse intensifies, however, the election of a Republican mayor does not cause an increase in the racial gap in arrests.

[16]Table 3.A.6, in the appendix, shows the results of our main specification, when we use a simpler measure of the intensity of the presidential rhetoric against drug abuse: the number of times the Presidents used the word *drug*, over the total number of words in the presidential papers in a given month.

Table 3.5.2: Effect of political competition on arrests for possession of cocaine and heroin - Bartik

	Dependent variable:			
	Arrests for possession of cocaine or heroin for Blacks			
	(1)	(2)	(3)	(4)
Pol. Comp. $\times$ Pres.Rhet.	0.0007***	0.0009***	0.0010***	0.0007**
	(0.0003)	(0.0002)	(0.0003)	(0.0003)
	Arrests for possession of cocaine or heroin for Whites			
Pol. Comp. $\times$ Pres.Rhet.	0.0005	-0.0000	-0.0001	-0.0001
	(0.0005)	(0.0003)	(0.0003)	(0.0003)
Agency FE	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes
State Time Trends FE	No	Yes	No	No
State x Year FE	No	No	Yes	Yes
Controls	No	No	No	Yes
Mean Outcome Blacks	0.3386	0.3386	0.3386	0.3386
Mean Outcome Whites	0.7058	0.7058	0.7058	0.7058
Observations	116,172	116,172	116,172	116,172

Notes: This table shows estimates of Equation 3.4 for arrests for possession of cocaine or heroin for Blacks (top panel) and Whites (bottom panel). The regressor of interest is the interaction between the prevalence of the topic drugs in the US President public papers (shift) and the continuous measure of political competition (share) at the county level. In order to make the interpretation of the coefficient easier, we multiple both measures by 100. Different columns report different specifications of Equation 3.4. Column 1 reports a specification with police agency and month by year fixed effects. In column 2 we add state specific linear time trends. In Column 3 we control for state by year fixed effects and in Column 4 we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Local Newspapers and the Presidential rhetoric Against Drug Abuse We provide evidence that counties that were more politically competitive were more exposed to the presidential rhetoric against drug abuse. Figure 3.6.1 plots the average number of monthly mentions of words related to the *War on Drugs Campaign* for different levels of political competition. In Figure 3.6.1 we include the average monthly mentions of the words *War on Drugs*, *Crack Cocaine*, *Willie Horton* and *Welfare Queen*. For all the words we plot the average mentions after the 1986 Anti Drug Abuse Act (in black) and before the 1986 Anti Drug Abuse Act (in grey), along with regression lines. For each word there is a clear positive relationship between political competition and the mentions of words related to the *War on Drugs*. This relationship holds both before and after the 1986 Anti Drug Abuse Act, however it is always stronger after the 1986 Anti Drug Abuse Act. The case of *Welfare Queen* is the only one in which the relationship is similar before and after the enactment of the 1986 Anti Drug Abuse Act. This is consistent with the term being used as a *dog whistle* before the 1986 Anti Drug Abuse Act (Haney-López, 2014). We obtain similar results when focus on survey data from the American National Election Studies (ANES). In particular, Figure 3.B.6, in the Appendix, reports the same results for the fraction of people who gave a positive answer to the question *did you see the Republican candidate on TV?*.

More formally, we test the effect of political competition on the exposure to the presidential rhetoric against drug abuse. To do this we estimate the following difference-in-differences model:

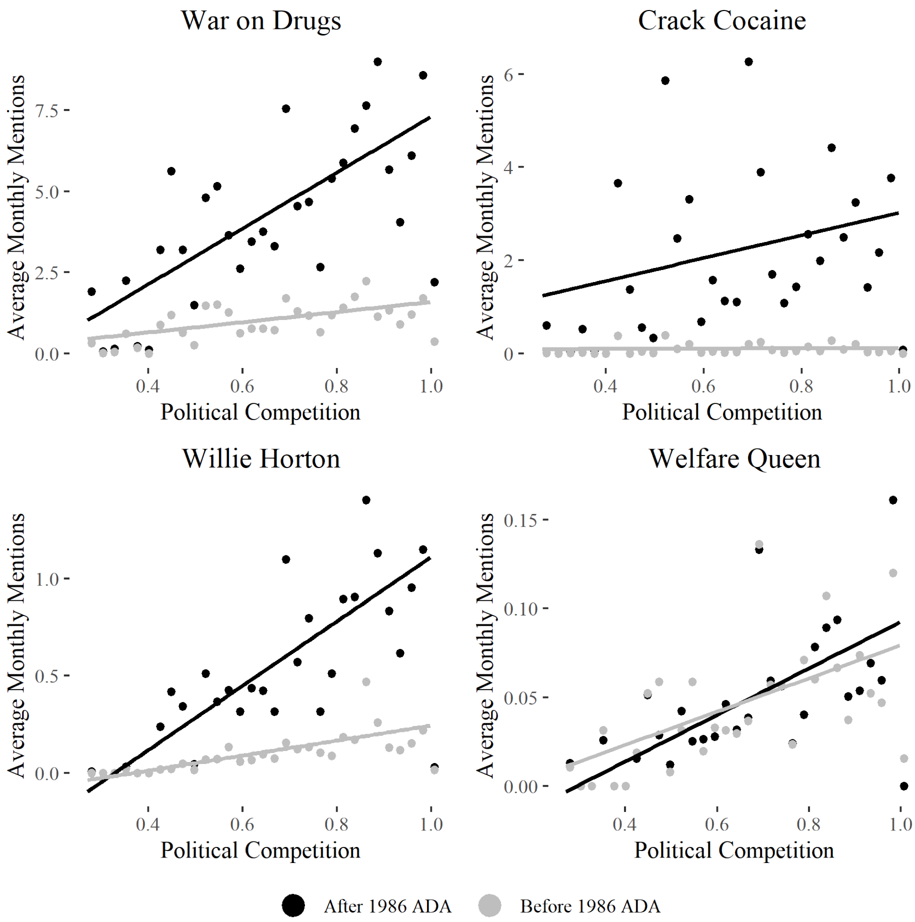
$$y_{ct} = \beta \text{Pol. Comp}_c \times \text{Post}_t + \delta_p + \delta_t + \delta_{sy} + \mathbf{X}_c \times \text{Post}_t + \epsilon_{ct}. \tag{3.5}$$

The model is identical to the one described in Equation 3.1, where the only difference is that we change the outcome to be the inverse hyperbolic sine transformation of the number of mentions of words related to presidential rhetoric against drug abuse for a local newspaper that is serving a specific county. Moreover, the sample is smaller, as we are only able to match a subset of counties for which we were able to find a local newspaper.

Table 3.6.1 shows the effects of being a politically competitive county after the start of the presidential rhetoric against drug abuse on the number of mentions of words related to the *War on Drugs*. [17] We estimate the model separately for the words *War*

[17] In the appendix, in Table 3.A.8 and Table 3.A.9 we conduct a similar exercise using both our measures of the intensity of the presidential rhetoric against drug abuse and the frequency of the use of the word *drug* in the Presidential public papers. This alternative designs answers directly the question: do local newspaper talk more about the *War on Drugs* in more politically competitive counties when the President talks more about drugs? The results are qualitatively similar to those shown in Table 3.6.1.

Figure 3.6.1: Mentions of Words Related to the War on Drugs



Notes: This Figure plots the correlation between the number of times local newspapers mention words related to the presidential rhetoric against drug abuse and the political competition in that counties before (in grey) and after (in black) the first Anti Drug Abuse (September 1986)

Table 3.6.1: Effect of political competition on presidential rhetoric on local Newspapers

	Dependent variable:					
	Ihs Count					
	(1)	(2)	(3)	(4)	(5)	(6)
	War on drugs	Just say no	Crack cocaine	Crack babies	Welfare queen	Willie Horton
Pol. Comp X Post	0.1195**	0.0139	0.1164**	0.0260**	0.0089	0.0503**
	(0.0566)	(0.0116)	(0.0567)	(0.0132)	(0.0057)	(0.0237)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	1.0177	0.0545	0.4242	0.0541	0.0443	0.2257
Observations	31,080	31,080	31,080	31,080	31,080	31,080

Notes: This table shows estimates of Equation 3.5 for the number of mentions of words related to the *War on Drugs*. The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed. Different columns report results for the different words: *War on Drugs*, *Just say no*, *Crack cocaine*, *Crack babies*, *Welfare queen* and *Willie Horton*. We show the most complete specification including police agency, month by year, state by year fixed effects and we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

on Drugs, *Just say no*,*Crack cocaine*, *Crack babies*, *Welfare queen* and *Willie Horton*. The estimated coefficients confirm the findings obtained by looking at Figure 3.6.1. All words show positive coefficients, with *Just say no* and *Welfare Queen* being the only two where we are not able to reject the null hypothesis of a zero effect. This comes as no surprise, as already in Figure 3.6.1 we showed that *welfare queen* was positively associated with political competition already before the 1986 Anti Drug Abuse Act.

Reagan Visits If the mechanism that drives the estimates of our main specification is the exposure to the presidential rhetoric against drug abuse, one would expect arrests for possession of crack cocaine to grow around Reagan's political rallies.

We estimate a triple differences model where we compare the racial gap in arrests for possession of crack cocaine between Blacks and Whites around Ronald Reagan's political rallies after 1986.[18] To account for the fact that Reagan visits different places at different points in time — i.e. staggered adoption — we implement the methodology proposed by (Borusyak, Jaravel and Spiess, 2021). These models are identical to our

[18]We estimate a model where treatment is assigned at the city level and where we include the same set of fixed effects and controls that we included in our main specification.

main specification, with the only difference that the treatment is assigned at the city level and not at the county level, as we are able to observe the exact city where the rally was held.

Figure 3.B.7, in the appendix, shows dynamic treatment effect estimates of our triple differences model. Estimates before Reagan's rallies are not statistically different from zero before the rally and are not statistically different from zero after the rally. During the month of Reagan's rally, however the racial gap in arrests increases by roughly 50 percentage points and is statistically different from zero. Figure 3.B.8 and Figure 3.B.9, in the Appendix, report the same results for two separate difference in differences model estimated separately for Blacks and Whites, where we show that, when a longer time period is considered, Reagan's visits have a persistent effect on arrests for possession of crack cocaine both for Blacks and Whites.

Disentangling the Effect of Reagan Visits and Exposure to the Presidential Rhetoric Political campaign rallies are generally held by Presidential candidates in competitive counties. This would lead to a big overlap between the areas where presidential candidates go for political rallies and our treated counties. We look at the intersection between these two categories and perform a horse-race between the two measures: political competitiveness and political rallies to see which is the one driving the results. We do this by interacting a dummy that takes value one if a county hosted a political rally by Reagan after 1986 with our DiD and triple DiD interaction terms. We perform this exercise both on our difference in differences model and on our triple differences model. The results are shown in Table 3.A.10, in the appendix. The coefficient on political competition after 1986 remains positive and similar to our main specifications, and the triple interaction with Reagan's visits is also positive and statistically significant. We interpret this result as evidence that Reagans's political rallies have exacerbated the effect of exposure to the presidential rhetoric against drug abuse but are not able to fully explain it.

Spillover on Municipal Elections If our estimates are the result of an increase in exposure to the presidential rhetoric against drug abuse in the areas that were more politically competitive, we should register a spillover on local elections. We merge our dataset with the data about municipal election results (de Benedictis-Kessner, 2018). We then only consider municipalities that had an election both between 1984 and 1986 and after 1986. We then compare the chances of a republican mayor being elected before and after 1986 in politically competitive versus non politically competitive findings. We report results of this exercise in Table 3.A.11 in the appendix, where we show that the probability of observing a republican winning mayoral elections is 28 percentage points higher in highly competitive places after the introduction of the September

1986 Anti Drug Abuse Act. We then compare arrests for possession for cocaine and heroin in municipalities where Republicans won by a small margin in a regression discontinuity setup (Eggers, Fowler, Hainmueller, Hall and Snyder Jr, 2015). We test whether electing a Republican mayor has a direct effect on arrests for possession of crack cocaine. Table 3.A.12 shows the results of this exercise. For both Blacks and Whites we can not reject the null hypothesis that a Republican mayor does not have a causal impact on the number of arrests for possession of cocaine or heroin. The results of these two exercises confirm that municipalities that were in counties that were more exposed to the presidential rhetoric experienced an increase in electoral campaigning, however, the election of Republican mayors is not able to explain the racial gap in arrests that results from this increase in exposure to the presidential rhetoric. The absence of a direct effect of electing a Republican mayor is also consistent with the absence of a *line of command* effect, whereby mayors collaborate with police agencies and re-direct their law enforcement effort towards the prosecution of crack cocaine crimes.

Effect on Changes in Attitudes Towards Blacks We posit that our effect is driven by a change in law enforcement behavior by police officers. Ideally, one would like to have a repeated survey that elicits officers' attitudes toward racial minorities. By comparing the attitudes of officers in areas that are more and less exposed to the presidential rhetoric against drug abuse, one would be able to understand if officers changed their view about minorities. We approximate this design by exploiting several questions contained in the ANES surveys from 1984 to 1990 that elicit attitudes of individuals towards minorities.[19] We then compare answers to these questions from individuals who were living in more or less competitive counties before and after the presidential rhetoric against drug abuse in a DiD framework. Table 3.A.13 reports the results of this exercise. The estimated coefficients reveal that individuals in counties that were more exposed to the presidential rhetoric against drug abuse started viewing Blacks less favorably. We interpret this result as evidence in favor of the hypothesis that law enforcement officers changed their law enforcement behavior as a consequence of being more exposed to the presidential rhetoric against drug abuse — under the assumption that the average police officer has similar beliefs to the average respondent to the ANES survey —-.

[19] We focus our attention on 5 questions: Black-thermometer (a value going from 0 to 97, where 0 means very bad feelings and 97 means very good feelings); "Past slavery and discrimination have created conditions that make it difficult for blacks their way out of the lower class"; "Blacks should not have special favors to succeed such as Irish, Italians and Jewish"; "Blacks gotten less than they deserve over the past few years"; "Blacks must try harder to succeed". For each of these questions we create a dummy variable taking value 1 if the respondent answered "Agree" or "Strongly Agree" and 0 when he/she answered "Disagree" or "Strongly Disagree". We exclude respondents interviewed by Blacks to avoid social desirability bias.

Discrimination: Taste Based, Statistical and Institutional A racial gap in arrests for possession of crack cocaine caused by exposure to the presidential rhetoric against drug abuse could be the result of taste based discrimination (Becker, 1971), statistical discrimination (Knowles, Persico and Todd, 2001) or institutional discrimination (Small and Pager, 2020) — or a combination of all three —. Our approach does not allow us to distinguish between these three different types of discrimination. Higher exposure to the presidential rhetoric against drug abuse could prompt police officers to patrol neighborhoods that have a higher share of Black individuals, under the assumption that race is a good proxy for crack cocaine consumption — statistical discrimination —. Higher exposure to the presidential rhetoric could embolden a taste based animus police officers, who gain some utility by arresting more Black Americans because they do not like them — taste based discrimination —.

Finally, the racial gap in arrests between Blacks and Whites could be caused by institutional discrimination. Institutional discrimination, as defined by Small and Pager (2020) is the *differential treatment by race that is either perpetrated by organizations or codified into law.* Institutional discrimination can be the consequence of statistical discrimination, essentially because disparities breed discrimination (Lang and Kahn-Lang Spitzer, 2020). In our context, the presidential rhetoric against drug abuse was heavily focused on crack cocaine, a drug that was strongly associated with Black communities. We can therefore expect that officers who were more exposed to the rhetoric concentrated their effort on patrolling neighborhoods with a higher density of Blacks, which generated the racial gap in arrests for possession of crack cocaine. In this case, we would have a clear example of institutional discrimination, whereby police officers do discriminate because race is considered a good predictor of usage, but the rhetoric –albeit being race-neutral – is clearly affecting Blacks more than Whites by heavily focusing on crack cocaine, despite the lack of medical evidence justifying the huge treatment disparity between crack cocaine and other drugs (Hatsukami and Fischman, 1996).

We test whether counties that have higher racial resentment experienced a higher increase in the racial gap in arrests for possession of crack cocaine. We follow (Acharya, Blackwell and Sen, 2016; Grosjean, Masera and Yousaf, 2022) and estimate heterogeneous treatment effects for areas that have higher racial resentment. In particular, we interact our treatment variable with the presence of enslaved people in 1860, cotton suitability — a commonly used exogenous predictor of slavery — and the inverse hyperbolic sign transformation of the number of lynchings of Black people — as a proxy racial violence in the Jim Crow era —.

Table 3.A.14 and Table 3.A.15, in the appendix, show the results of this exercise both for our differences in differences identification strategy and our reduced form Bartik

approach. We do not find any evidence that the effect of the presidential rhetoric against drug abuse is magnified by racial resentment. The coefficient for the interaction of our treatment variable and the three measures of racial resentment is always negative, and our main treatment effect always remains positive and statistically significant. We report our main effect and the marginal effect for counties with higher racial resentment in figures Figure 3.B.10 and Figure 3.B.11 in the appendix. These results show that the effect of exposure to the presidential rhetoric against drug abuse on arrests for possession of crack cocaine is entirely driven by counties with low racial resentment. We interpret these findings as evidence that police officers were using race as a proxy for crack cocaine usage. This finding is compatible both with statistical and institutional discrimination.

3.7 Robustness

Political competition can impact arrests for crack cocaine through a different causal path than the one we hypothesized. It is possible, for example, that officers who live in counties that experience more political competition feel pressured to exert a stronger effort in fighting crime, independently from the presidential rhetoric against drug abuse. In that case, our estimates would reflect the effect of political competition in itself. Moreover, political competition can be correlated to several unobservable characteristics of counties that also correlate with crime. For example, counties that are more politically competitive have more individuals below the poverty line. If economic conditions harden, and individuals in these counties get unemployed they might resort to crime as an alternative source of income. In this case, our estimates would be biased, as they would reflect the impact of a tighter labor market on poorer areas. This bias would arise because political competition is correlated with poverty, and economic conditions harden at the same time as the presidential rhetoric against drug abuse becomes more intense.

In these scenarios, however, one would expect that arrests for other crimes than for crack cocaine would increase as well. If law enforcement officers become tougher because of political competition, they should arrest more people for other crimes as well. If individuals resort to crime because economic conditions harden and more politically competitive counties are poorer, one would expect property crimes and prostitution to increase as well. In particular, Grogger and Willis (2000) estimate that the arrival of crack cocaine in American cities caused both violent and property crimes to increase.

We test whether our treatment had an effect on a battery of crime-related outcomes and find no positive statistically significant effect. We interpret this as evidence that

Table 3.7.1: Other Crime Outcomes - DiD

	(1) Robbery Blacks	(2) Robbery Whites	(3) Prostitution Blacks	(4) Prostitution Whites	(5) DUI Blacks	(6) DUI Whites	(7) Murder Blacks	(8) Murder Whites	(9) Mtr Veh Theft Blacks	(10) Mtr Veh Theft Whites
Pol. Comp x Post	-0.0192	-0.0137	-0.0057	0.0012	0.0239	0.0079	-0.0041	-0.0046	0.0201	-0.0353**
	(0.0126)	(0.0103)	(0.0109)	(0.0108)	(0.0152)	(0.0278)	(0.0070)	(0.0063)	(0.0170)	(0.0180)
Agency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	0.3531	0.4254	0.1469	0.2147	0.6646	2.8986	0.0772	0.1101	0.2817	0.6905
Observations	116,172	116,172	116,172	116,172	116,172	116,172	116,172	116,172	116,172	116,172

Notes: This table shows estimates of Equation 3.1 for arrests for crime not related with drug possession. The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed. Different columns report different crime outcomes for Blacks and for Whites. We show the most complete specification including police agency, month by year, state by year fixed effects and we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

the increase in arrests for possession of heroin and cocaine is indeed not related to an underlining differential trend in crime. Moreover, we show that no other type of crime displayed significantly diverging trends between treated and control counties either before or after the 1986 ADA. We interpret this finding as evidence that the underlying factors that cause criminal behavior did not drastically change in treated counties in a different way than in control counties.

Effect on Other Crimes We test whether political competition has an impact on other crimes than arrests for possession of crack cocaine after the 1986 ADAA. Table 3.7.1 shows estimates of equation Equation 3.1 – our DD identification strategy – for robbery, prostitution, driving under the influence, murder and motor vehicle theft for both Blacks and Whites. Table 3.A.16, in the appendix, reports the same results for estimates of Equation 3.4 – our Bartik-type approach –. The results of this exercise show that in both cases no other crime experienced a statistically significant increase, with arrests for motor vehicle thefts for Whites being the only result that is statistically significant – with a point estimate of -0.03 – at the 5% level for our DD specification. These results show that other crimes besides arrests for possession of crack cocaine for Blacks did not increase. Moreover, Figure 3.B.12, in the appendix, shows dynamic treatment effect estimates for robbery, prostitution, driving under the influence, murder and motor vehicle theft for both Blacks and Whites. We can notice that all outcomes do not display significant deviations in trends between treatment and control counties both before and after the passage of the 1986 ADAA. This evidence is consistent with our results being driven by higher exposure to the presidential rhetoric against drug

Table 3.7.2: Other Type of Drugs - DiD

	(1) Cannabis Blacks	(2) Cannabis Whites	(3) Synthetic Narc Blacks	(4) Synthetic Narc Whites	(5) Other Drugs Blacks	(6) Other Drugs Whites
Pol. Comp x Post	0.0127	-0.0268	0.0022	-0.0240*	0.0183	-0.0588
	(0.0151)	(0.0257)	(0.0070)	(0.0144)	(0.0206)	(0.0419)
Agency FE	Yes	Yes	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	0.3337	1.1257	0.0230	0.0872	0.1124	0.3920
Observations	116,172	116,172	116,172	116,172	116,172	116,172

Notes: This table shows estimates of Equation 3.1 for arrests for possession of other type of drugs (different from heroin and cocaine). The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed. Different columns report the different type of drugs for Blacks and for Whites. We show the most complete specification including police agency, month by year, state by year fixed effects and we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

abuse and not by differences in unobservable determinants of criminal activity.

Effect on Other Type of Drugs We test whether political competition has an impact on other crimes than arrests for possession of crack cocaine after the 1986 ADAA. Table 3.7.2 shows estimates of Equation 3.1 – our DD identification strategy – for marijuana, synthetic drugs and other drugs for both Blacks and Whites. Table 3.A.17, in the appendix, reports the same results for estimates of Equation 3.4– our Bartik-type approach –. The results of this exercise show that in both cases no other type of drug experienced a statistically significant increase at the 5% level. Moreover, Figure 3.B.13, in the appendix, shows dynamic treatment effect estimates for possession of marijuana, synthetic drugs, and other drugs for both Blacks and Whites. All outcomes do not display significant deviations in trends between treatment and control counties both before and after the passage of the 1986 ADA. This evidence is consistent with our results being driven by higher exposure to the presidential rhetoric against drug abuse This evidence is consistent with our results being driven by higher exposure to the presidential rhetoric against drug abuse, specifically against crack cocaine, and not by differences in unobservable determinants of illicit drugs trading.

Federal Grants Financing the War on Drugs The presidential rhetoric against drug abuse could affect arrests for crack cocaine through a different channel than a change in the enforcement behavior of law enforcement officers. It is possible that police agencies in more competitive counties experienced an increase in federal funding. If that would be the case, our estimates would incorporate the effect of an increase in funding as well. We overcome this issue by testing whether agencies in more politically competitive counties experienced an increase in the number of police officers. Table 3.A.18, in the appendix, shows the results of estimating Equation 3.1 and Equation 3.4 on the number of employees per capita in the police agencies in our sample with a breakdown by gender and by role (officer/administrative). The results show that the number of employees per capita did not increase in the treated units compared the controlled ones. These results are in line with police officers re-directing their law enforcement behavior when exposed to the presidential rhetoric against drug abuse and go against the alternative explanations that the counties that we considered as treated experienced an increase in funding.[20]

Selection in Reporting and Covariates Our dataset uses police agencies as a unit of observation. We do this as we are only able to observe some agencies continuously reporting to the UCR program throughout our sample period. Some of the variables that we include as controls, and most importantly our treatment, are measured at the county level. If there is some selection on these variables in reporting to the UCR program and these variables are heterogeneously distributed in space within counties, our estimates could be biased. We re-estimate our main specifications on a subset of counties for which the population that agencies in our sample cover in 1980 – when we have precise census data about the population at the county level – is higher than the 80% of the population of the county. Table 3.A.19, in the appendix, reports estimates of Equation 3.1 and Equation 3.4 obtained after restricting the sample following the criteria described above. Results are qualitatively similar to those obtained in our main specification, showing a statistically significant positive effect for Blacks and no statistically significant effect for Whites.

Sensitivity to 1984 Elections The 1984 presidential election was a very unusual election. Reagan won by a huge margin and one could expect that places that were electorally competitive in that election are not electorally competitive in a different election. We address this concern by estimating our main specification using measures of political competition that are obtained from election results in 1972, 1976, 1980 and an average of 1972-1984 elections. Table 3.A.20 and Table 3.A.21, in the appendix, show the results of our main specifications, when we use different elections to calculate political competition. The results of this exercise show that our estimates remain

[20] Cox and Cunningham (2021) Analyse Byrne grants, the main federal funds targeted at combating illicit drugs, and find that cities and states that got funded by these grants experienced an increase in police officers and in arrests for the sale of illicit drugs for Blacks, but not an increase for possession of illicit drugs, irrespectively from ethnicity.

largely unchanged when using other elections to proxy for political competition. The sizes of our estimated coefficients are similar in magnitude to the estimated coefficients in our main specification and are always positive and statistically significant for Blacks and never statistically different from zero for Whites.

The only exception is the estimated coefficient for our DD model estimated with the 1976 election, which is still positive but smaller in size and not statistically different from 0. We attribute this difference to the fact that, if anything, the 1976 election was even more idiosyncratic than the 1984 election. The 1976 election came after the 1974 Watergate scandal and saw many southern states vote democratic for this election only. This argument becomes clear when looking at Figure 3.B.14, where we show that the measure of political competition at the county level is strongly correlated for the 1988, 1984 and 1972 elections, but the correlation is less strong when we consider the 1976 presidential elections.

Rates, Shares and Zeroes Our main specification uses the inverse hyperbolic sine transformation of the number of arrests as the outcome variable. We show that our estimates are robust to alternative specifications of the outcome variable and to estimators that better perform with a large prevalence of zeroes. In Table 3.A.22, in the appendix, we show that our estimates increase in magnitude and are still statistically significant if we estimate our main specification using the Poisson pseudo-maximum-likelihood estimator (Silva and Tenreyro, 2006). Moreover, in table Table 3.A.23, in the appendix, we show that our estimates are robust to alternative specifications of the outcome variable. In particular, we estimate our main specifications on the number of arrests for possession of cocaine and heroin over the total arrests for possession of cocaine and heroin (columns one and two), the total arrests for possession of cocaine and heroin for Whites, the total number of arrests for possession of any drug, and the total number of arrests for any crime. Overall, this exercise shows that our estimates are not sensitive to alternative choices of the dependent variable. Finally, we use the arrest rate by race as our outcome variable, we implement this analysis on our restricted sample where can observe at least 80% of the population within a county. This choice is motivated by the fact that we can only observe ethnic composition at the county level. Table 3.A.24, in the appendix, reports the results of this exercise. We find positive effects of the presidential rhetoric against drug abuse on arrests for possession of cocaine or heroin for Blacks, however, for our Bartik-type approach, we are not able to reject the null of the absence of an effect of the presidential rhetoric against drug abuse on arrests for possession of cocaine or heroin for Blacks. We attribute the absence of statistical significance to the smaller sample size, due to the loss of observations caused by the fact that we can not observe more than 80% of the population for all the counties in our data.

Different Rhetoric for Republicans and Democrats A potential concern with our conceptual framework is that, in theory, counties that face higher political competition could be less exposed to the presidential rhetoric against drug abuse. This would be true, for example, if individuals who live in more competitive counties are exposed to opposing rhetoric about illicit drug abuse. One could hypothesize, that while Republicans adopted a *tough on crime* rhetoric, democrats were more inclined to a more rehabilitative approach, therefore *diluting* the Republican *tough on crime* rhetoric. We exploit data on congressional speeches to show that Republicans and Democrats talked about illicit drugs at the same time and in a remarkably similar way. Figure 3.B.15 and Figure 3.B.16, in the appendix, show the number of times that the word *drug* has been used in the Congressional speeches of the House of Representatives and of the Senate during our sample period.[21] It can be noticed that the black and grey lines, indicating Republicans and Democrats, are essentially overlapping, showing that Republicans and Democrats congressmen talked about drugs at the same time and with the same intensity. Moreover, we run an *A La Carte* (ALC) embedding analysis (ALC) (Khodak et al., 2018; Rodriguez, Spirling and Stewart, 2021), to check what are the words that are more often associated with the word *drug* by Republicans and Democrats. Figure 3.B.17, in the appendix, plots the probability that a specific words is associated with the word *drug* in congressional speeches. The horizontal axis shows the probability for Republicans and the vertical axis shows the probability for Democrats. If the probability that a given word is associated to the word *drug* is the same for both Republicans and Democrats the word will lie on the 45° line. It can be noticed that all words lie extremely close to the 45° line, indicating that Republicans and Democrats talked in a similar way about illicit drugs.

Sensitivity to *Tough on Crime* Another concern is that agencies that are located in more politically competitive counties are more responsive to any shock that is affecting illicit drugs consumption, or the toughness of law enforcement against drug crimes. We overcome this concern by showing that we only find an effect immediately after the 1988 ADAA and the 1988 presidential campaign, even when we follow police agencies until 2010. Figure 3.B.18, in the appendix, shows estimates of Equation 3.2, where we estimate treatment effects until December 2010. Equation 3.2 shows that our treatment effect estimates start growing after the 1986 ADAA, peak after the 1988 ADAA and presidential elections, and then decrease shortly after that and remain constant and close to zero after that until the end of 2010, even if the topic of illicit drugs has had constant attention from the general public even after that.[22] These results are consis-

[21]the number is divided by the number of speakers for each party to account for the fact that democrats tended to have more speakers during our sample period.

[22]We show that illicit drugs have been a relevant topic in the public discourse throughout the decades after the end of our sample period. Figure 3.B.19, in the appendix, plots the number of

tent with estimates of our main specification reflecting the impact of the presidential rhetoric against drug abuse on the behavior of law enforcement officers.

3.8 Conclusion

While a large literature has studied how much the criminal justice system can be racially biased, little is known about the impact of political campaigning on racial discrimination by law enforcement officers. Recent literature has shown how Trump's presidential rhetoric has triggered anti-minority behaviors in individuals (Müller and Schwarz, 2020; Feinberg, Branton and Martinez-Ebers, 2022) and discriminatory behavior by law enforcement officers (Grosjean, Masera and Yousaf, 2022). In this paper, we show that the exposure to political campaigning and to the presidential rhetoric against drug abuse influenced law enforcement behavior way before the Trump era and right at the start of the large historical racial disparity in arrests for drugs that have characterized the US during the last century.

We find those police agencies that were more exposed to political campaigning and to the presidential rhetoric against drug abuse between 1986 and 1990, experienced a sharp increase in arrests for possession of heroin and cocaine for Blacks— also when accounting for baseline drug prevalence and differences in determinants of drug abuse, as well as state specific policies—, while arrests for Whites did not increase significantly. We create a new measure of the intensity of the presidential rhetoric against drug abuse through text analysis algorithms that we apply to the corpus of speeches, statements and official papers released by Presidents Reagan and Bush senior. We find that when the presidential rhetoric against drug abuse is stronger, arrests for possession of crack cocaine increase in counties that are more exposed to the presidential rhetoric against drug abuse. Consistently with our effect being completely driven by the exposure to the presidential rhetoric against drug abuse, we do not find any effect on arrests for other types of crime that are normally associated with the consumption of crack cocaine, such as murder and robberies, nor on arrests for other types of drugs. We ensure that our effect is driven by political campaigning by running a triple differences model where we compare arrests for possession of crack cocaine for Blacks and Whites in places where Reagan held a political rally after 1986. We find that in the month of a Reagan rally, the racial gap in arrests increases by 50%, with no statistically significant difference between arrests for Blacks and Whites both before and after Reagan's rallies.

We show that the effect of the presidential rhetoric against drug abuse is not driven by counties that had a higher racial resentment at baseline. This result goes against the interpretation that the presidential rhetoric against drug abuse between 1986 and

mentions of the word *drugs* in books available from google books.

1990 is driven by taste-based discrimination (Becker, 1971). We interpret this result as evidence that the presidential rhetoric against drug abuse induced police officers to use race as a signal for the probability of using crack cocaine, a behavior that is consistent with statistical discrimination (Knowles, Persico and Todd, 2001). We argue that this discriminatory behavior, albeit resulting from the belief that Blacks are more likely to consume crack cocaine, stems from institutional discrimination. The presidential rhetoric heavily focused on crack cocaine and codified the punitive approach against crack cocaine in the 1986 and 1988 ADAA, despite the lack of medical evidence of crack cocaine being more dangerous than other drugs (Hatsukami and Fischman, 1996).

This study shows that politicians need to carefully consider the potentially discriminatory implications of their policy platform. We provide evidence that the presidential rhetoric against drug abuse that Reagan and Bush sr. developed during the second half of the 80's resulted in a sizeable racial gap in arrests for possession of crack cocaine. Our results are specific to the political situation in the US in the 80s, but still provide general insights on how a *tough on crime* rhetoric and political platform can contribute to exacerbate racial inequalities. These findings are particularly relevant in the current policy debate, especially with respect to the recent attacks to *Capitol Hill* and the protests by the *Black Lives Matter* movement.

Appendices

3.A Tables

Table 3.A.1: Summary Statistics

	Level	Observations	Mean	SD	Min	Max
Ihs possession heroin or coke blacks	Agency-Month	116,172	0.339	0.931	0	4.605
Ihs possession heroin or coke whites	Agency-Month	116,172	0.706	1.246	0	4.970
Vote Share 1984 Presidential Election	County-1984	116,172	0.757	0.148	0.379	0.994
Dummy Political Competition	County-1984	116,172	0.552	0.497	0	1
Drugs Topic Weight	US-Month	116,172	0.049	0.015	0.027	0.094
Share female	County-1980	116,172	0.511	0.011	0.474	0.534
Share pop over 18	County-1980	116,172	0.677	0.031	0.580	0.747
Share under 10	County-1980	116,172	0.148	0.021	0.105	0.221
Percent below poverty level	County-1980	116,172	0.117	0.049	0.036	0.297
Share black	County-1985	116,172	0.089	0.109	0	0.452
Crack index	State-1980	116,172	0.686	0.501	-0.045	1.542
Population	Agency-Year	116,172	47,365.378	100,852.282	2,871	489,749

Notes: This table shows the summary statistics of our main variables.

Table 3.A.2: Balance Table In/Out Sample

Variable	(1) Out of Sample N	Mean/SE	(2) In Sample N	Mean/SE	Normalized difference (1)-(2)
population	2202	40.120	662	180.967	-0.582
		(2.393)		(17.210)	
share under 10	2202	0.155	662	0.150	0.185
		(0.000)		(0.001)	
share pop 10-18	2202	0.176	662	0.177	-0.092
		(0.000)		(0.001)	
share pop over 18	2202	0.670	662	0.672	-0.073
		(0.001)		(0.001)	
share female	2202	0.508	662	0.511	-0.168
		(0.000)		(0.000)	
share black	2202	0.080	662	0.087	-0.054
		(0.003)		(0.005)	
percent below poverty level	2201	0.166	662	0.126	0.553
		(0.002)		(0.002)	
political_competition	2202	0.450	662	0.500	-0.101
		(0.011)		(0.019)	

Notes: This table shows the mean, the standard error and the normalized difference for counties that are in our sample and counties that are not.

Table 3.A.3: Balance Table Political Competition treated/control

	Below Median Pol. Comp.		Above Median Pol. Comp.		Normalized difference
Variable	N	Mean/SE	N	Mean/SE	(1)-(2)
population	331	139.765 (13.891)	331	222.169 (31.357)	-0.186
share under 10	331	0.152 (0.001)	331	0.149 (0.001)	0.139
share pop 10-18	331	0.178 (0.001)	331	0.177 (0.001)	0.015
share pop over 18	331	0.671 (0.002)	331	0.674 (0.002)	-0.102
share female	331	0.509 (0.001)	331	0.513 (0.001)	-0.352
share black	331	0.067 (0.005)	331	0.108 (0.008)	-0.329
percent below poverty level	331	0.112 (0.002)	331	0.140 (0.003)	-0.519

Notes: This table shows the mean, the standard error and the normalized difference for counties that are in our treatment group and counties that are in our control group.

Table 3.A.4: Triple Differences Estimates

	Dependent variable:			
	Arrests for possession of cocaine or heroin			
	(1)	(2)	(3)	(4)
Pol.Comp. × Post × Black	0.0405	0.1114***	0.1139***	0.0801***
	(0.0407)	(0.0262)	(0.0263)	(0.0269)
Agency FE	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes
State Time Trends FE	No	Yes	No	No
State x Year FE	No	No	Yes	Yes
Controls	No	No	No	Yes
Mean Outcome	0.5222	0.5222	0.5222	0.5222
Observations	232,344	232,344	232,344	232,344

Notes: This table shows estimates of Equation 3.3 (triple DiD) for arrests for possession of cocaine or heroin. The regressor of interest is the triple interaction between the dummy measure of political competition at the county level, a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed and a dummy representing the race. Different columns report different specifications of equation 3.3. Column 1 reports a specification with police agency and month by year fixed effects. In column 2 we add state specific linear time trends. In Column 3 we control for state by year fixed effects and in Column 4 we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.5: Effect of political competition on arrests for possession of cocaine on heroin - Different UCR cleaning

	Arrest rate for possession of cocaine or heroin			
	(1)	(2)	(3)	(4)
	Blacks		Whites	
	No Cleaning	Mello (2019)	No Cleaning	Mello (2019)
Political Comp X Post	0.0259***	0.0219***	0.0116*	0.0098
	(0.0069)	(0.0066)	(0.0065)	(0.0061)
Bartik-type	0.0002***	0.0001**	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Agency FE	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	751,804	799,932	751,804	799,932

Notes: This table reports estimates of Equation 3.1 and Equation 3.4 obtained using the UCR without cleaning procedures (columns 1 and 3) and using the Mello (2019) UCR dataset cleaning process (columns 2 and 4). The outcome variables are computed as the ihs of the number of arrests for Blacks (columns 1 and 2) or for Whites (columns 3 and 4). The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed (up panel). While in bottom panel we use as main regressor our Bartik reduced form. We show results using the most complete specification including police agency, month by year and state by year fixed effects, and controlling for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.6: Bartik Reduced Form with Share Word Drug

	Dependent variable:	
	Arrests for possession of cocaine or heroin	
	(1) Blacks	(2) Whites
Bartik-share word drug	0.0171***	0.0044
	(0.0064)	(0.0065)
Agency FE	Yes	Yes
Month x Year	Yes	Yes
State x Year FE	Yes	Yes
Controls	Yes	Yes
Observations	116,172	116,172

Notes: This table reports estimates of Equation 3.4. The outcome variables are computed as the ihs of the number of arrests for Blacks (column 1) or for Whites (column 2). The regressor of interest is the a Bartik reduced form computed as the interaction of a continuous variable representing the share of time the word "drug" has been used by the presidents in their public paper and our continuous variable for political competition. Both variables are multiplied by 100 to simplify the interpretation of the coefficient. We show results using the most complete specification including police agency, month by year and state by year fixed effects, and controlling for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.7: Triple Differences Estimates - Bartik

	Dependent variable:			
	Arrests for possession of cocaine or heroin			
	(1)	(2)	(3)	(4)
Bartik-type	0.0002	0.0009***	0.0010***	0.0008***
	(0.0005)	(0.0003)	(0.0003)	(0.0003)
Agency FE	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	No
State Time Trends FE	No	Yes	No	No
State x Year FE	No	No	Yes	Yes
Controls	No	No	No	Yes
Observations	232,344	232,344	232,344	232,344

Notes: This table shows estimates of Equation 3.3 (triple differences) for arrests for possession of crack cocaine. The regressor of interest is the interaction between the prevalence of the topic drugs in the US President public papers (shift) and the continuous measure of political competition (share) at the county level. Different columns report different specifications of Equation 3.3. Column 1 reports a specification with police agency and month by year fixed effects. In column 2 we add state specific linear time trends. In Column 3 we control for state by year fixed effects and in Column 4 we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.8: Effect of political competition and presidential rhetoric on local Newspapers - Intensity of presidential rhetoric

	Dependent variable:					
	Ihs Count					
	(1)	(2)	(3)	(4)	(5)	(6)
	War on drugs	Just say no	Crack cocaine	Crack babies	Welfare queen	Willie Horton
Bartik-type	0.0016***	0.0002**	0.0008	0.0004**	-0.0001	0.0003
	(0.0005)	(0.0001)	(0.0005)	(0.0002)	(0.0001)	(0.0002)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	1.0177	0.0545	0.4242	0.0541	0.0443	0.2257
Observations	31,080	31,080	31,080	31,080	31,080	31,080

Notes: This table shows estimates of Equation 3.5 for the number of mentions of words related to the *War on Drugs*. Different columns report results for the different words: *War on Drugs*, *Just say no*, *Crack cocaine*, *Crack babies*, *Welfare queen* and *Willie Horton*. The regressor of interest is the interaction between the prevalence of the topic drugs in the US President public papers (shift) and the continuous measure of political competition (share) at the county level. In order to make the interpretation of the coefficient easier, we multiple both measures by 100. We show the most complete specification including county, year-month, state by year fixed effects and we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.9: Effect of political competition on presidential rhetoric on local Newspapers - Share of the word drug in presidential papers

	Dependent variable:					
	Ihs Count					
	(1)	(2)	(3)	(4)	(5)	(6)
	War on drugs	Just say no	Crack cocaine	Crack babies	Welfare queen	Willie Horton
Bartik-share word drug	0.0633***	0.0051	0.0333***	0.0070*	-0.0006	-0.0049
	(0.0176)	(0.0033)	(0.0123)	(0.0036)	(0.0016)	(0.0050)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean Outcome	1.0177	0.0545	0.4242	0.0541	0.0443	0.2257
Observations	31,080	31,080	31,080	31,080	31,080	31,080

Notes: This table shows estimates of Equation 3.5 for the number of mentions of words related to the *War on Drugs*. Different columns report results for the different words: *War on Drugs*, *Just say no*, *Crack cocaine*, *Crack babies*, *Welfare queen* and *Willie Horton.* The regressor of interest is the a Bartik reduced form computed as the interaction of a continuous variable representing the share of time the word "drug" has been used by the presidents in their public paper and our continuous variable for political competition. Both variables are multiplied by 100 to simplify the interpretation of the coefficient. We show the most complete specification including county, year-month, state by year fixed effects and we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.10: DiD and Triple Differences Estimates interacted with places visited by Reagan

	Dependent variable:	
	Arrests for possession of cocaine or heroin	
	(1) Blacks DiD	(2) Triple DiD
Pol.Comp x Post	0.0563*	
	(0.0313)	
Pol.Comp x Post x Black		0.0753***
		(0.0268)
Pol.Comp x Post x Reagan visit	0.7067**	
	(0.2631)	
Pol.Comp x Post x Black x Reagan visit		0.3402**
		(0.1702)
Agency FE	Yes	Yes
Month x Year	Yes	Yes
State x Year	Yes	Yes
Controls	Yes	Yes
Observations	116,172	232,344

Notes: This table report results of the interaction of our main DiD treatment with a dummy identifying those places visited by Reagan after 1986 (column 1), and of our triple DiD treatment interacted with the same dummy. We show results using the most complete specification including police agency, month by year and state by year fixed effects, and controlling for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.11: Effect of political competition on Municipal Elections

	(1) Mayor Rep	(2) Mayor Rep
Pol Comp Pres X Post	0.1562*	0.2751**
	(0.0888)	(0.1110)
Population	Yes	Yes
Place FE	Yes	Yes
Election Year FE	Yes	No
State x Election Year FE	No	Yes
Mean Outcome	0.3548	0.3548
Observations	436	436

Notes: This table show results for the probability to have a Republican mayors in places in county highly competitive after the September 1986 Anti Drug Abuse Act. We consider only municipalities that had an election both between 1984 and 1986 and after 1986. The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed. In column 1 we include place, election year fixed effects and we control for the population in the place. While in column 2 we include state x year fixed effects. Standard errors are clustered at the place level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.12: The Effect of a Republican Mayor
RD Estimates

	Arrests for possession of cocaine or heroin	
	(1) Blacks	(2) Whites
Republican Mayor	0.0445	-0.1920
	(0.4025)	(0.2808)
Observations	2,015	2,015

Notes: This table reports estimates of regression discontinuity design where the running variable is the republican margin of victory for a municipal election and the outcome is the inverse hyperbolic sine transformation of arrests for possession of cocaine or heroin. Standard errors are clustered at the municipality level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.13: Effect of political competition and war on drugs on attitudes towards Blacks

	Dependent variable:				
	ANES answer attitudes towards Blacks				
	(1)	(2)	(3)	(4)	(5)
	Black Thermometer 0-100	Dummy Agree Past slavery and discrimination have created current negative conditions for Blacks	Dummy Agree Blacks should not have special favors to succeed such as Irish, Italians and Jewish	Dummy Agree Blacks gotten less than they deserve over the past few years	Dummy Agree Blacks must try harder to succeed
Pol.Comp. X Post	-2.190**	-0.0617	0.0566	-0.1044**	0.0839**
	(1.103)	(0.0459)	(0.0420)	(0.0477)	(0.0357)
County FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	6,422	2,840	2,843	2,473	2,737

Notes: This table reports estimates of Equation 3.1. From ANES data from 1984 to 1990 we exploit 5 different questions from this survey data. In column (1), we report results using the Black thermometer score as outcome (a value going from 0 to 97, where 0 means very bad feelings and 97 means very good feelings); in column (2) we use a dummy variable taking value 1 if the respondent agree with the sentence "Past slavery and discrimination have created conditions that make it difficult for blacks their way out of the lower class"; in column (3) we use a dummy variable taking value 1 if the respondent agree with the sentence "Blacks should not have special favors to succeed such as Irish, Italians and Jewish"; in column (4) we use a dummy variable taking value 1 if the respondent agree with the sentence "Blacks gotten less than they deserve over the past few years"; and in column (5) we use a dummy variable taking value 1 if the respondent agree with the sentence "Blacks must try harder to succeed" The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed. We show results controlling for county and year fixed effects and removing from the sample all the individuals interviewed by a Black interviewer. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.14: Heterogeneity by taste based discrimination - DiD

Arrest for possession of cocaine or heroin for Blacks			
	(1)	(2)	(3)
Pol. Comp x Post	0.0719**	0.2504***	0.1068***
	(0.0323)	(0.0622)	(0.0395)
Pol. Comp x Post x Lynchings	-0.0572		
	(0.0390)		
Pol. Comp x Post x Cotton Suitability		-0.3608**	
		(0.1444)	
Pol. Comp x Post x Any Slaves			-0.1512**
			(0.0611)
Agency FE	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	116,172	71,652	95,256

Notes: This table shows results for the taste based discrimination. The outcome variable is the number of arrests for possession of cocaine or heroin for Blacks. We interact our DiD treatment with three different predetermined county characteristics that proxy taste based discrimination. In column (1) we interact our treatment with the IHS of the number of lynchings of Blacks; in column (2) with the presence of slaves in 1860; and in column (3) with a variable expressing the soil suitability for growing cotton (Acharya, Blackwell and Sen (2016)). In the three columns we are including police agency, month by year fixed effects and state by year fixed effects. We control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.15: Heterogeneity by taste based discrimination - Bartik

Arrest for possession of cocaine or heroin for Blacks			
	(1)	(2)	(3)
Bartik	0.0007**	0.0016***	0.0006*
	(0.0003)	(0.0004)	(0.0003)
Bartik x Lynchings	-0.0002**		
	(0.0001)		
Bartik x Cotton Suitability		-0.0004	
		(0.0004)	
Bartik x Any Slaves			-0.0004**
			(0.0001)
Agency FE	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Observations	116,172	71,652	95,256

Notes: Notes: This table shows results for the taste based discrimination. The outcome variable is the number of arrests for possession of cocaine or heroin for Blacks. We interact our Bartik type reduced form with three different predetermined county characteristics that proxy taste based discrimination. In column (1) we interact our treatment with the IHS of the number of lynchings of Blacks; in column (2) with the presence of slaves in 1860; and in column (3) with a variable expressing the soil suitability for growing cotton. In the three columns we are including police agency, month by year fixed effects and state by year fixed effects. We control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.16: Other Crime Outcomes - Bartik

	(1) Robbery Blacks	(2) Robbery Whites	(3) Prostitution Blacks	(4) Prostitution Whites	(5) DUI Blacks	(6) DUI Whites	(7) Murder Blacks	(8) Murder Whites	(9) Mtr Veh Theft Blacks	(10) Mtr Veh Theft Whites
Bartik-type	0.0000	-0.0001	0.0001	0.0002**	0.0001	0.0000	0.0000	-0.0001	0.0002*	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Agency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,172	116,172	116,172	116,172	116,172	116,172	116,172	116,172	116,172	116,172

Notes: This table shows estimates of Equation 3.4 for arrests for crime not related with drug possession. The regressor of interest is the interaction between the prevalence of the topic drugs in the US President public papers (shift) and the continuous measure of political competition (share) at the county level. We show results with police agency, month by year and state by year fixed effects we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.17: Other Type of Drugs - Bartik

	(1) Cannabis Blacks	(2) Cannabis Whites	(3) Synthetic Narc Blacks	(4) Synthetic Narc Whites	(5) Other Drugs Blacks	(6) Other Drugs Whites
Bartik-type	0.0001	-0.0002	-0.0000	-0.0001*	0.0000	-0.0005
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0004)
Agency FE	Yes	Yes	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,172	116,172	116,172	116,172	116,172	116,172

Notes: This table shows estimates of Equation 3.4 for arrests for possession of other type of drugs (different from heroin and cocaine). The regressor of interest is the interaction between the prevalence of the topic drugs in the US President public papers (shift) and the continuous measure of political competition (share) at the county level. We show results with police agency, month by year and state by year fixed effects we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.18: Effect on Law Enforcement Personnel

	(1) Employees	(2) Female Employees	(3) Male Employees	(4) Civilian Employees	(5) Civilian Female	(6) Civilian Male	(7) Officers	(8) Female Officers	(9) Male Officers
Pol. Comp X Post	-0.0026	-0.0008	-0.0019	-0.0006	-0.0006	-0.0000	-0.0020	-0.0002	-0.0018
	(0.0028)	(0.0011)	(0.0021)	(0.0027)	(0.0011)	(0.0019)	(0.0020)	(0.0004)	(0.0018)
Bartik-type	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Agency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,172	116,172	116,172	116,172	116,172	116,172	116,172	116,172	116,172

Notes: This table shows estimates of Equation 3.1 and Equation 3.4 for the number of law enforcement personel. The outcome variables are computed as the share of law enforcement employees with respect the population of the police agency. We show results using the most complete specification including police agency, month by year and state by year fixed effects, and controlling for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level.

Table 3.A.19: Effect of Political Competition - Restricted Sample

	Arrest for possession of crack cocaine			
	(1)	(2)	(3)	(4)
	Black		White	
Political Comp X Post	0.1233**		0.0282	
	(0.0535)		(0.0500)	
Bartik-type		0.0014**		0.0001
		(0.0006)		(0.0006)
Agency FE	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	44,688	44,688	44,688	44,688

Notes: This table reports estimates of Equation 3.1 and Equation 3.4 obtained after restricting the sample to counties where we observe more than 80% of the population. The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed (columns 1 and 3). While in columns 2 and 4 we use as main regressor our Bartik reduced form. We show results using the most complete specification including police agency, month by year and state by year fixed effects, and controlling for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.20: Effect of political competition in previous Presidential elections (1972-1980) on arrests for possession of cocaine or heroin - DiD

	Dependent variable:			
	Arrests for possession of cocaine or heroin for Blacks			
	(1)	(2)	(3)	(4)
Pol. Comp. 1972 X Post	0.0757**			
	(0.0350)			
Pol. Comp. 1976 X Post		0.0250		
		(0.0316)		
Pol. Comp. 1980 X Post			0.0793***	
			(0.0305)	
Pol. Comp. Av. 1972 1984 X Post				0.0916***
				(0.0321)
	Arrests for possession of cocaine or heroin for Whites			
Pol. Comp. 1972 X Post	0.0180			
	(0.0291)			
Pol. Comp. 1976 X Post		-0.0193		
		(0.0327)		
Pol. Comp. 1980 X Post			0.0161	
			(0.0284)	
Pol. Comp. Av. 1972 1984 X Post				0.0064
				(0.0317)
Agency FE	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean Outcome Blacks	0.3386	0.3386	0.3386	0.3386
Mean Outcome Whites	0.7058	0.7058	0.7058	0.7058
Observations	116,088	116,172	116,172	116,088

Notes: This table shows estimates of Equation 3.1 for arrests for possession of cocaine or heroin for Blacks (top panel) and Whites (bottom panel). The regressor of interest is the interaction between the dummy measure of political competition for different Presidential elections (1972, 1976, 1980 and average 1972-1984) at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed. We report our main specification with police agency and month by year fixed effects; we control for state by year fixed effects and for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.21: Effect of political competition in previous Presidential elections (1972-1980) on arrests for possession of cocaine or heroin - Bartik

	Dependent variable:			
	Arrests for possession of cocaine or heroin for Blacks			
	(1)	(2)	(3)	(4)
Pol. Comp. 1972 X Pres.Rhet.	0.0006**			
	(0.0002)			
Pol. Comp. 1976 X Pres.Rhet.		0.0008**		
		(0.0003)		
Pol. Comp. 1980 X Pres.Rhet.			0.0010***	
			(0.0003)	
Pol. Comp. Av. 1972 1984 X Pres.Rhet.				0.0013***
				(0.0004)
	Arrests for possession of cocaine or heroin for Whites			
Pol. Comp. 1972 X Pres.Rhet.	0.0001			
	(0.0003)			
Pol. Comp. 1976 X Pres.Rhet.		-0.0001		
		(0.0003)		
Pol. Comp. 1980 X Pres.Rhet.			0.0001	
			(0.0003)	
Pol. Comp. Av. 1972 1984 X Pres.Rhet.				0.0000
				(0.0005)
Agency FE	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Mean Outcome Blacks	0.3386	0.3386	0.3386	0.3386
Mean Outcome Whites	0.7058	0.7058	0.7058	0.7058
Observations	116,088	116,172	116,172	116,088

Notes: This table shows estimates of Equation 3.4 for arrests for possession of cocaine or heroin for Blacks (top panel) and Whites (bottom panel). The regressor of interest is the interaction between the prevalence of the topic drugs in the US President public papers (shift) and the continuous measure of political competition for different Presidential elections (1972, 1976, 1980 and average 1972-1984) (share) at the county level. In order to make the interpretation of the coefficient easier, we multiple both measures by 100. We report our main specification with police agency and month by year fixed effects; we control for state by year fixed effects and for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.22: Poisson Model

	Arrest for possession of cocaine or heroin			
	(1)	(2)	(3)	(4)
	Blacks		Whites	
Political Comp X Post	0.3980**		0.0554	
	(0.1583)		(0.0780)	
Bartik-type		0.0022***		0.0003
		(0.0005)		(0.0004)
Agency FE	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	80,412	80,412	111,492	111,492

Notes: This table reports estimates of Equation 3.1 and Equation 3.4 using a Poisson model for count data. The outcome variables are the number of arrests for possession of cocaine and heroin for Blacks or Whites. The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed (columns 1 and 3). While in columns 2 and 4 we use as main regressor our Bartik reduced form. We show results using the most complete specification including police agency, month by year and state by year fixed effects, and controlling for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

Table 3.A.23: Different Outcome Variable Choice

	Share of Blacks arrests for possession of cocaine or heroin							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Over Total arrests for Possession of cocaine	Over Total arrests for Possession of cocaine	Over Total arrests for Whites	Over Total arrests Whites	Over Total arrests for Drugs possession	Over Total arrests for Drugs possession	Over Total arrests	Over Total arrests
Political Comp X Post	0.0122*		0.1365**		0.0094*		0.0041*	
	(0.0073)		(0.0541)		(0.0049)		(0.0023)	
Bartik-type		0.0002***		0.0011***		0.0001***		0.0000**
		(0.0001)		(0.0004)		(0.0000)		(0.0000)
Agency FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	116,172	116,172	116,172	116,172	116,172	116,172	116,172	116,172

Notes: This table shows results for the share of Blacks arrested for possession of cocaine or heroin. We construct different shares: number of Blacks arrested for possession of cocaine over total arrests for possession of cocaine (columns 1 and 2); number of Blacks arrested for possession of cocaine over number of Whites arrested for possession of cocaine (columns 3 and 4); number of Blacks arrested for possession of cocaine over number of arrests for drug possession(columns 5 and 6); number of Blacks arrested for possession of cocaine over number of arrests (columns 7 and 8). The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed (columns 1, 3, 5, 7). While in columns 2, 4, 6 and 8 we use as main regressor our Bartik reduced form. We show results with police agency, month by year and state by year fixed effects we control for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

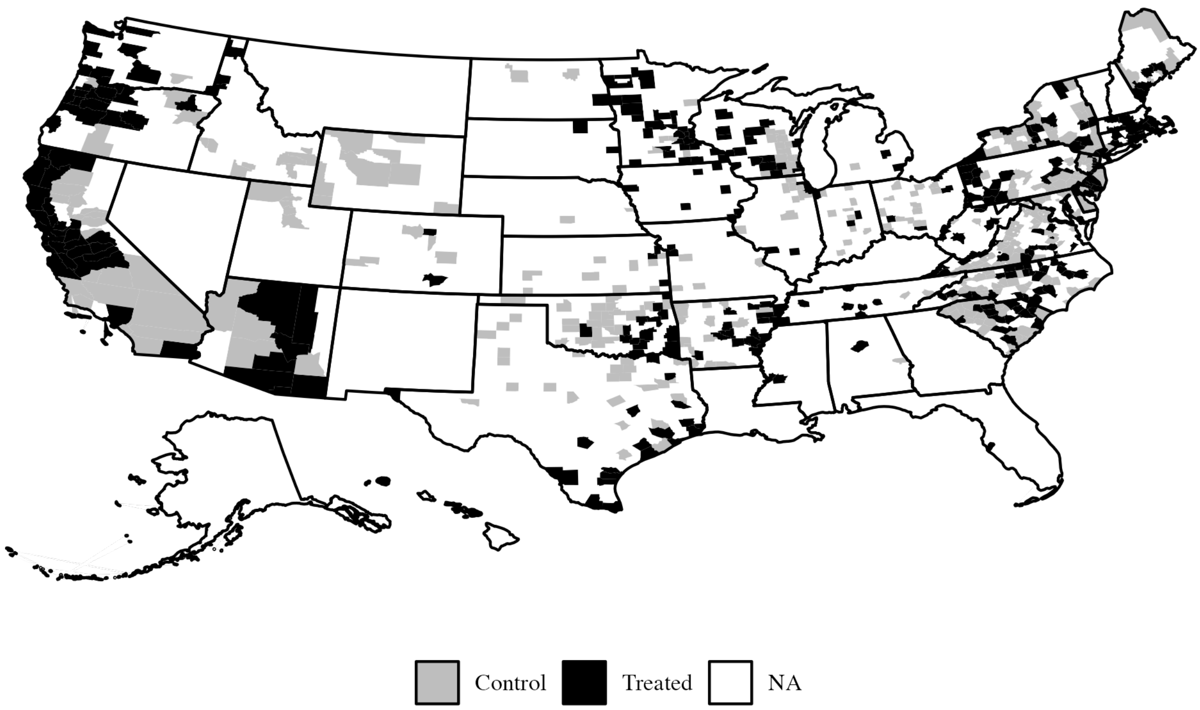
Table 3.A.24: Effect of campaigning on arrest rate by race

	Arrest rate for possession of cocaine or heroin			
	(1)	(2)	(3)	(4)
	Blacks		Whites	
Political Comp X Post	13.2708**		0.3847	
	(6.3225)		(0.9181)	
Bartik-type		0.0995		-0.0048
		(0.0714)		(0.0078)
Agency FE	Yes	Yes	Yes	Yes
Month x Year	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	44,688	44,688	44,688	44,688

Notes: This table reports estimates of Equation 3.1 and Equation 3.4 obtained after restricting the sample to counties where we observe more than 80% of the population. The outcome variables are computed as the number of arrests for Blacks (columns 1 and 2) or for Whites (columns 3 and 4) over the total Black or White population. The regressor of interest is the interaction between the dummy measure of political competition at the county level and a dummy for months after September 1986, the date in which the first Anti Drug Abuse act was passed (columns 1 and 3). While in columns 2 and 4 we use as main regressor our Bartik reduced form. We show results using the most complete specification including police agency, month by year and state by year fixed effects, and controlling for the population in the agency and non parametric controls for crack prevalence at the state level, black share, female share, share of population under 10 and over 18, share of population below the poverty level at the county level. Standard errors are clustered at the county level. *p<0.1; **p<0.05; ***p<0.01

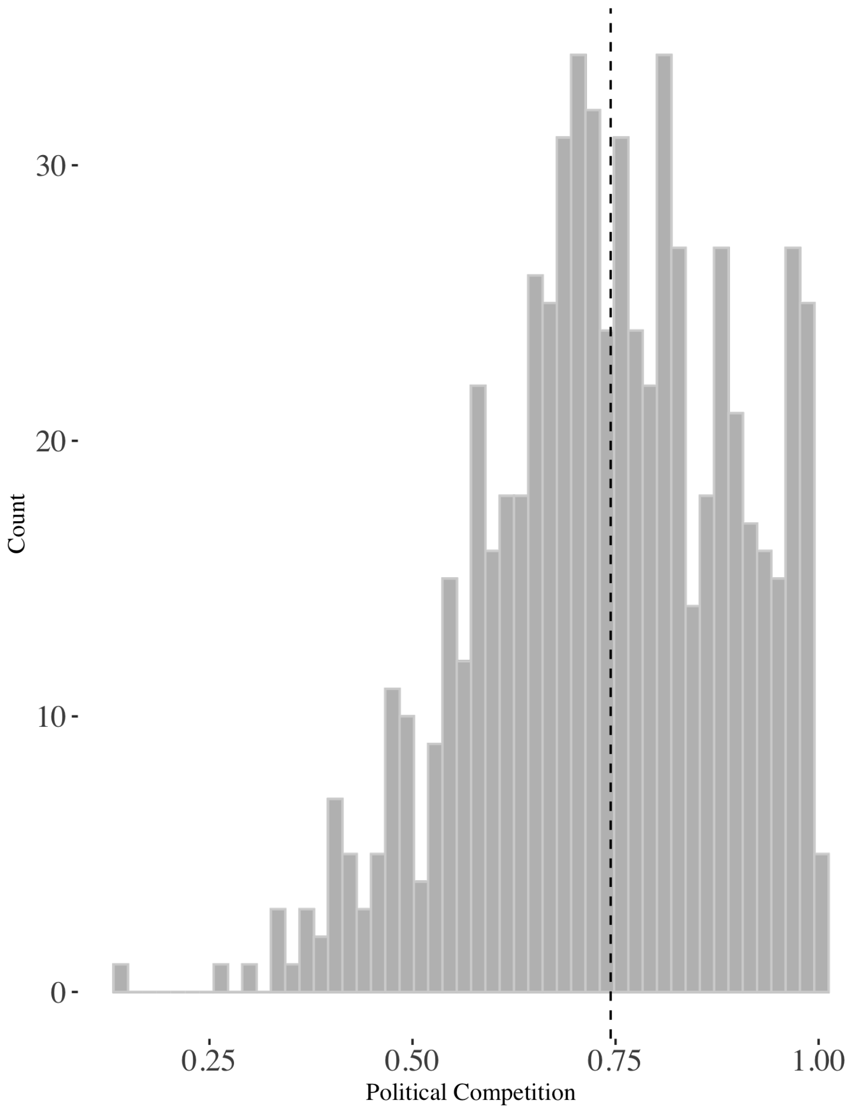
3.B Figures

Figure 3.B.1: Treated and Control Counties Map



Notes: This map plots treated and control counties.

Figure 3.B.2: Histogram of Political Competition

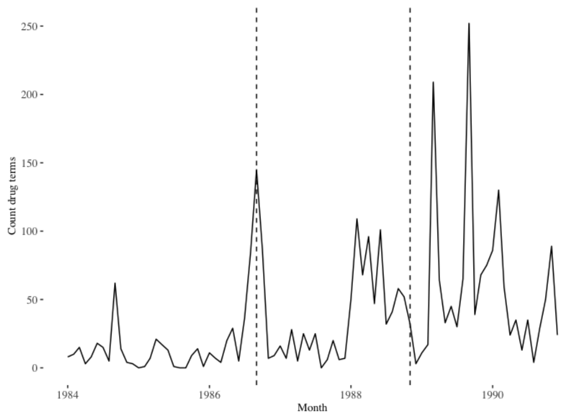


Notes: This graph shows the histogram of political competition. The dashed black line indicates the median level of political competition (0.74).

Figure 3.B.3: Topic Model - Public Papers by President Reagan and Bush

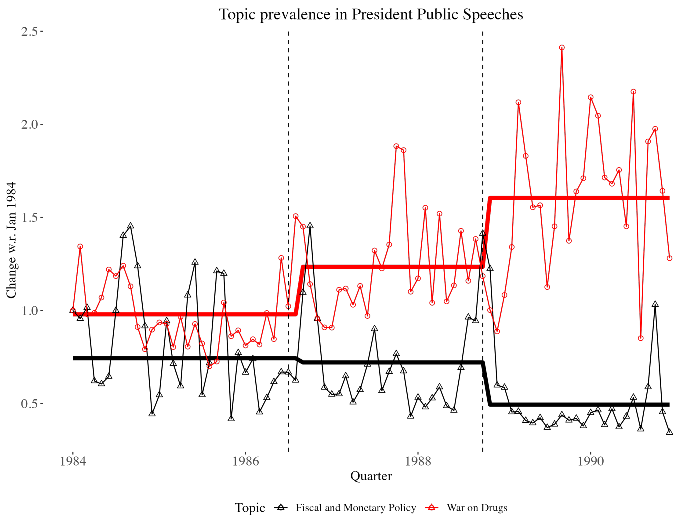
Notes: This graph shows the different topics identified by the LDA model on the corpus of the public papers by President Reagan and Bush from 1984 to 1990. Topic number 10 is our topic of interest: drugs.

Figure 3.B.4: Number of times the word drug is used in Reagan and Bush public papers



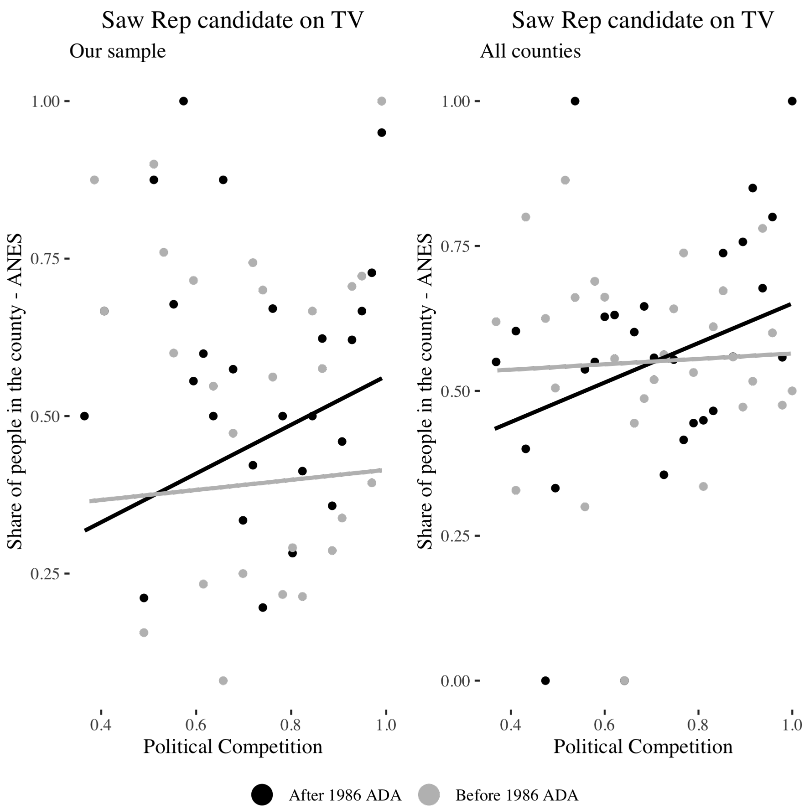
Notes: This graph plots the number of times the word drug is used by Reagan or Bush over time in their public papers. The dashed line are respectively the 1986 and 1988 ADAA

Figure 3.B.5: The Evolution of the Relevance of Drugs and Economy and Trade topics



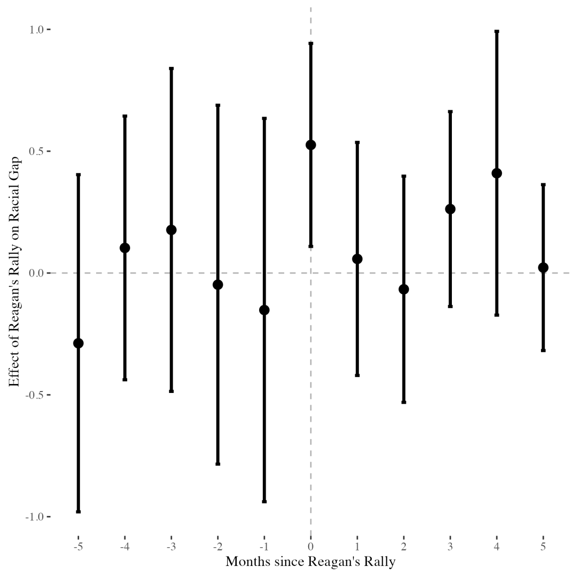
Notes: This graph shows the comparison between the importance of the drug topic over time with the economy and trade topic.

Figure 3.B.6: ANES



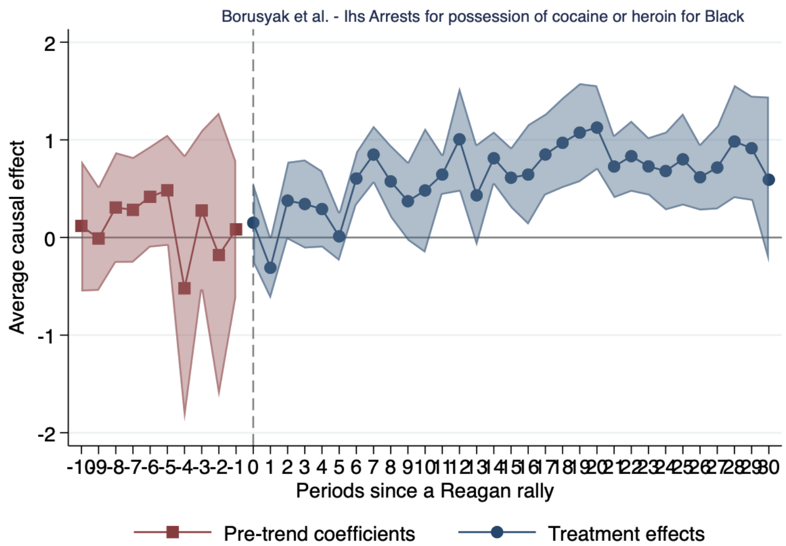
Notes: The figure shows that in highly competitive counties the probability to see a candidates on TV is higher. Using ANES survey data we show how our measure of political competition positive correlates with the probability to see a Republican candidate on TV after 1986 ADAA, while there is not correlation before the policy implementation. On the left we show this correlation using our sub-sample of counties, while on the right we show it exploiting the entire sample provided by ANES.

Figure 3.B.7: Arrests for possession of cocaine or heroin after a Reagan visit - Triple DiD



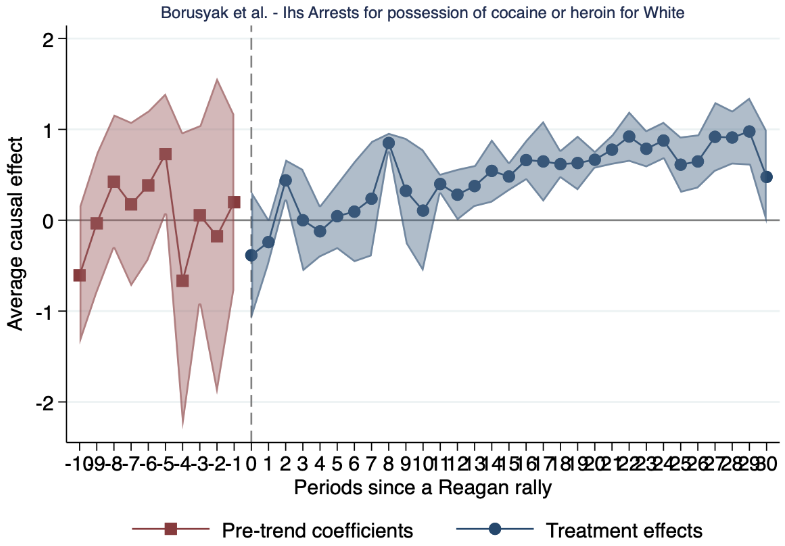
Notes: This graph shows dynamic treatment effect estimates of the effect of a Reagan visit after 1986 on the racial gap in arrests, estimated through a dynamic triple differences specification. The dashed black vertical lines indicate a Reagan visit after the 1968 Anti Drug Abuse Act. The gray lines show 95% confidence intervals for standard errors clustered at the county level.

Figure 3.B.8: Borusyak et all. (2021) - Arrest for possession of cocaine or heroin Blacks after a Reagan visit



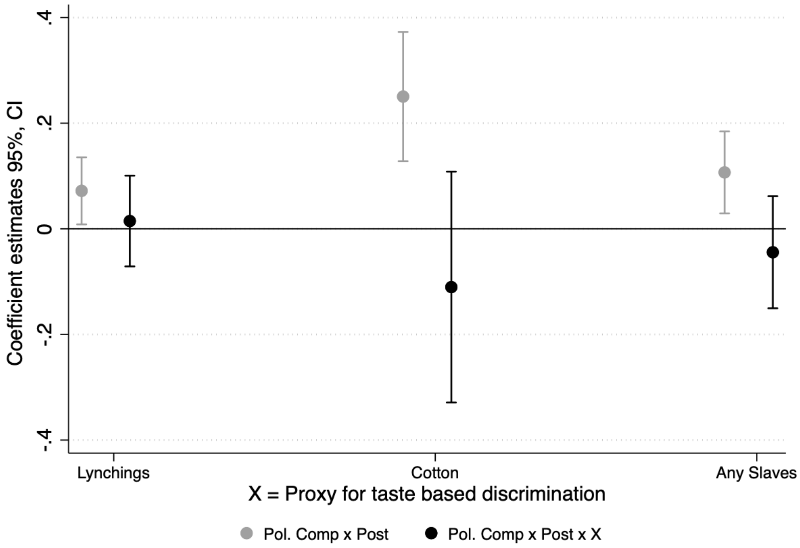
Notes: This graph shows dynamic treatment effect estimates using the Borusyak et all. (2021) machinery of the effect of a Reagan visit after 1986 ADAA on arrests for possession of heroin and cocaine for Whites. The dashed black vertical lines indicate the timing of the Reagan's visit. The gray lines show 95% confidence intervals for standard errors clustered at the county level.

Figure 3.B.9: Borusyak et all. (2021) - Arrest for possession of cocaine or heroin Whites after a Reagan visit



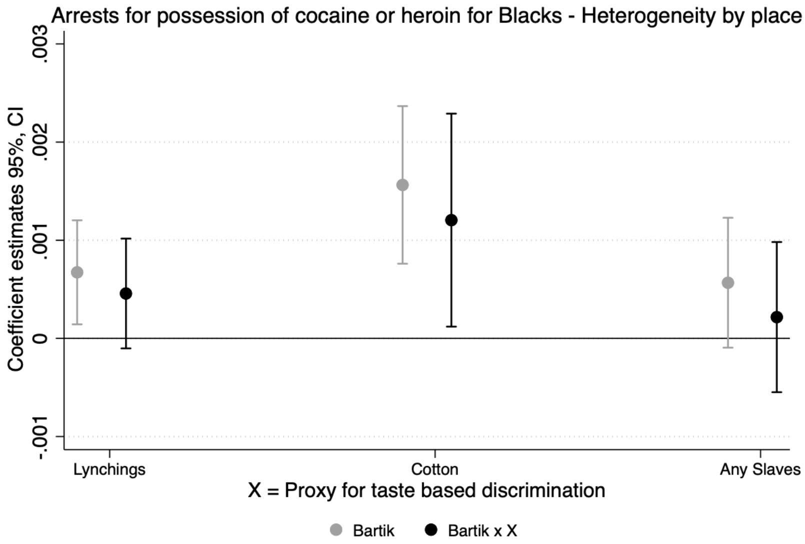
Notes: This graph shows dynamic treatment effect estimates using the Borusyak et all. (2021) machinery of the effect of a Reagan visit after 1986 ADAA on arrests for possession of heroin and cocaine for Blacks. The dashed black vertical lines indicate the timing of the Reagan's visit. The gray lines show 95% confidence intervals for standard errors clustered at the county level.

Figure 3.B.10: Heterogeneity by taste based discrimination - DiD



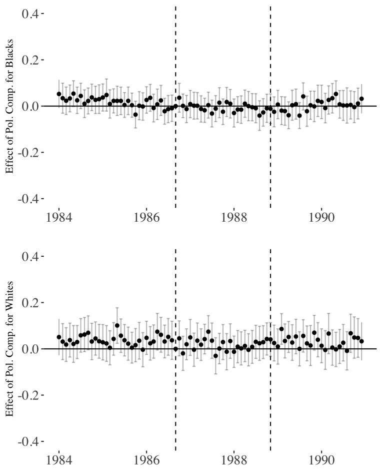
Notes: This figure show heterogeneity by taste based discrimination. In grey we report estimates for places with a lower taste based discrimination. In black we report the estimates for places with higher taste based discrimination. We estimates these coefficients by interacting our DiD treatment with each measure of taste based discrimination. We proxy taste based discrimination using: IHS of the number of lynchings of Blacks, soil suitability for growing cotton and presence of slaves in 1860 (Acharya, Blackwell and Sen (2016)).

Figure 3.B.11: Heterogeneity by taste based discrimination - Bartik

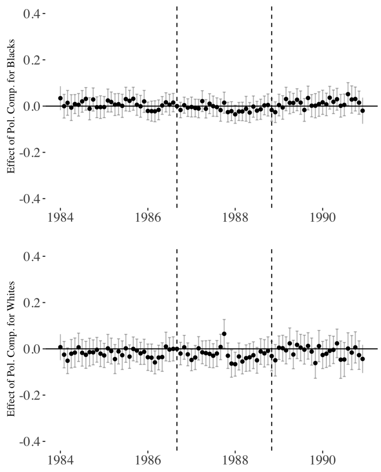


Notes: This figure show heterogeneity by taste based discrimination. In grey we report estimates for places with a lower taste based discrimination. In black we report the estimates for places with higher taste based discrimination. We estimates these coefficients by interacting our Bartik reduced form with each measure of taste based discrimination. We proxy taste based discrimination using: IHS of the number of lynchings of Blacks, soil suitability for growing cotton and presence of slaves in 1860 (Acharya, Blackwell and Sen (2016)).

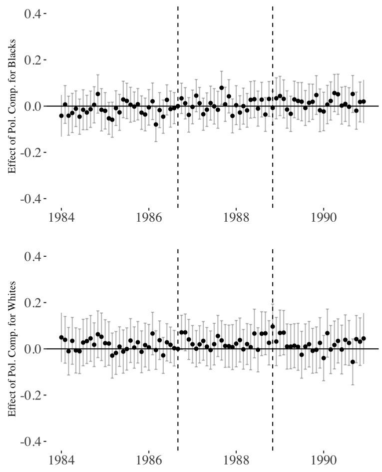
Figure 3.B.12: Event Study - Other Crime Outcomes



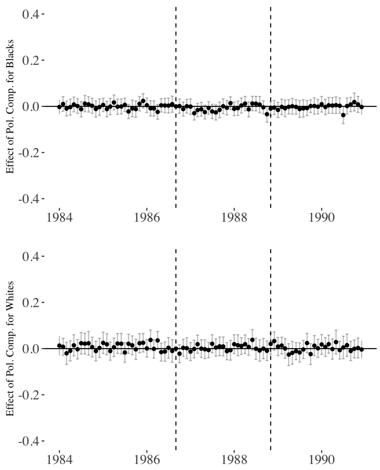
(a) *Robbery*



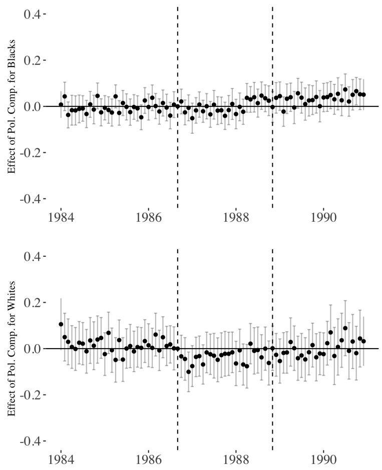
(b) *Prostitution*



(c) *DUI*



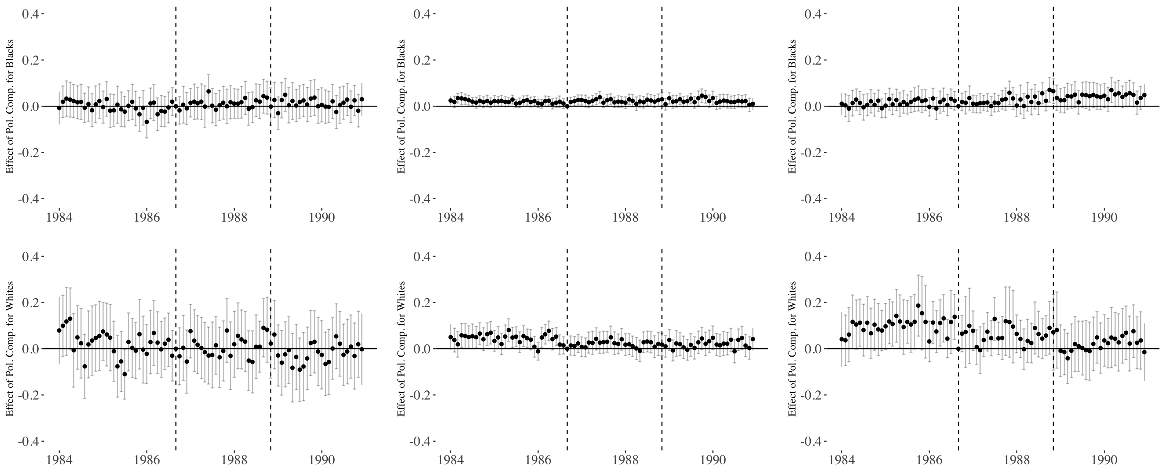
(d) *Murder*



(e) *Mtr Veh Theft*

Notes: This graph shows dynamic treatment effect estimates of the effect of political competition on arrests for all the other crime outcomes (robbery, prostitution, DUI, murder and Motor vehicle theft) for Blacks (Panel A) and for Whites (Panel B). The dashed black vertical lines indicate the enactment of the 1968 Anti Drug Abuse Act and the 1988 Anti Drug Abuse Act (which coincided with the 1988 elections). The gray lines show 95% confidence intervals for standard errors clustered at the county level.This graph plots the event study

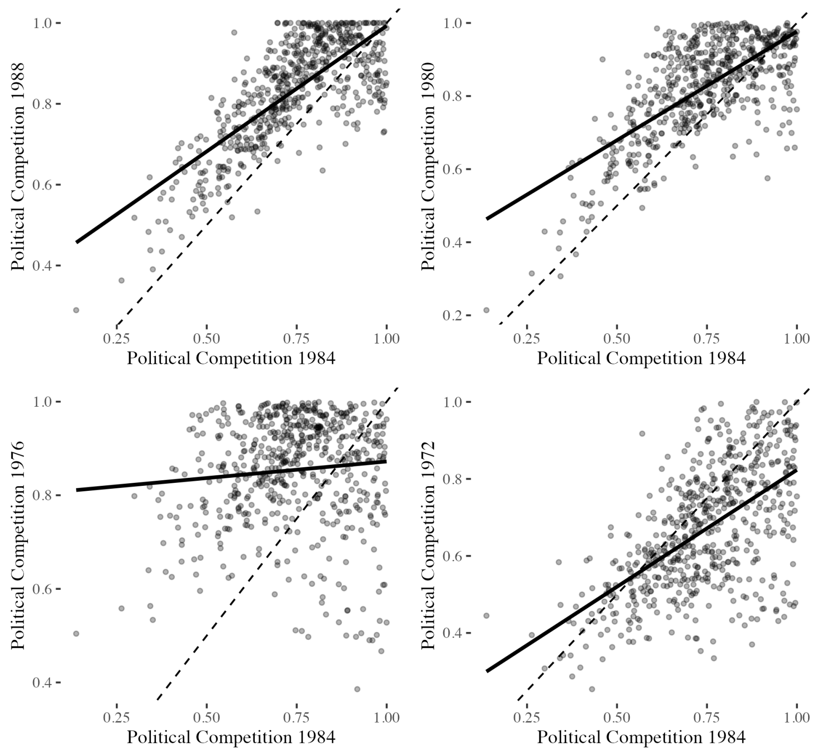
Figure 3.B.13: Event Study - Other Type of Drugs



(a) *Cannabis* **(b)** *Synthetic Narc* **(c)** *Other Drugs*

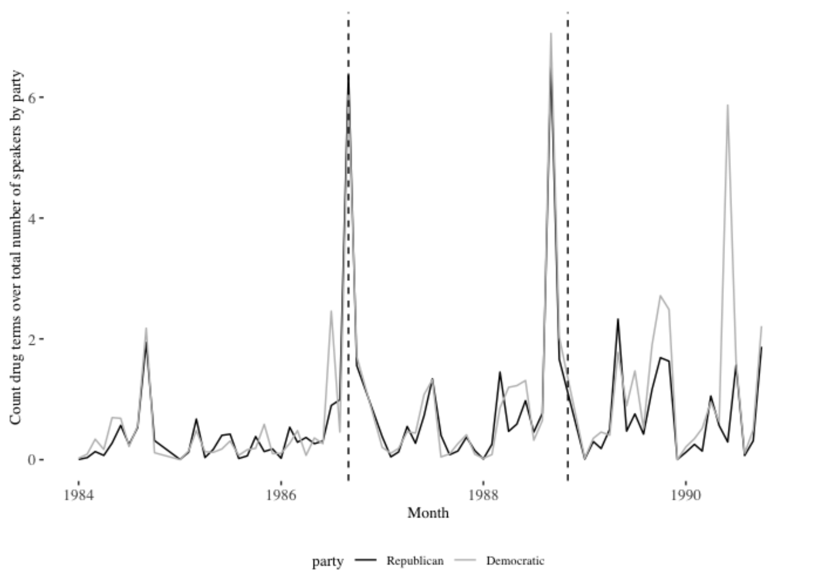
Notes: This graph shows dynamic treatment effect estimates of the effect of political competition on arrests for possession of other type of drugs (cannabis, synthetic, other drugs) for Blacks (Panel A) and for Whites (Panel B). The dashed black vertical lines indicate the enactment of the 1968 Anti Drug Abuse Act and the 1988 Anti Drug Abuse Act (which coincided with the 1988 elections). The gray lines show 95% confidence intervals for standard errors clustered at the county level.This graph plots the event study

Figure 3.B.14: Political competition in other elections



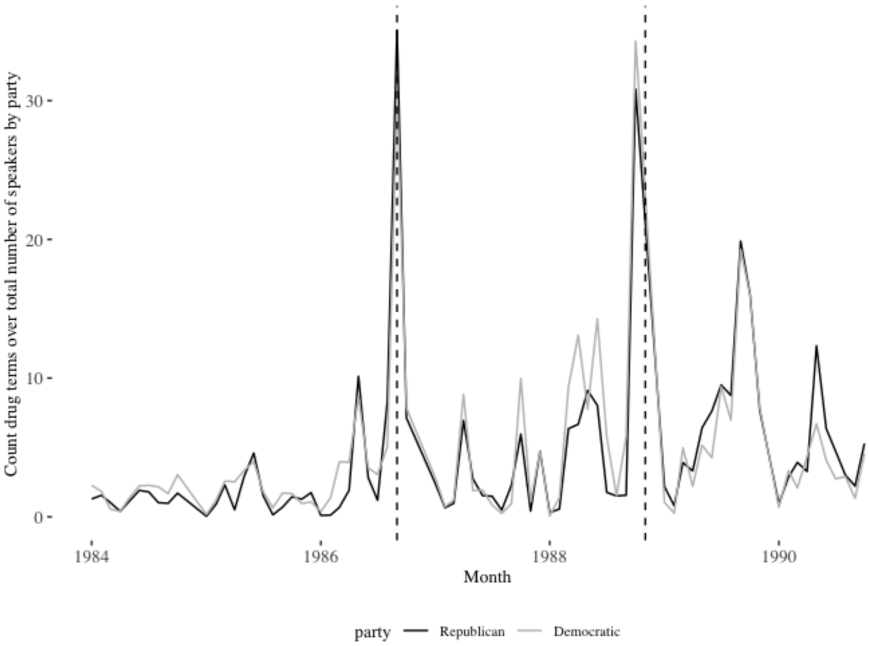
Notes: This figure plots the value for political competition across different elections. The solid black lines represent regression lines, the dashed black lines represent a 45 degree line.

Figure 3.B.15: Relative frequency of the drug word - House of Representatives



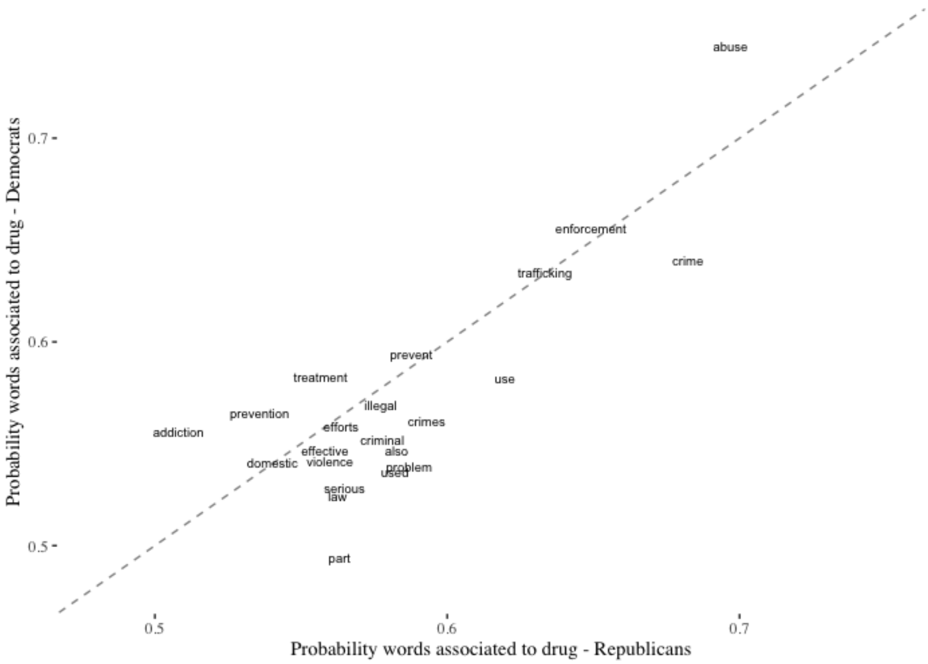
Notes: This graph shows the number of times that the word drug has been used in the Congressional speeches of the House of Representatives from January 1984 to December 1990 over the number of speakers by party. In black we present this relative frequency for the Republican party, and in grey for the Democratic party

Figure 3.B.16: Relative frequency of the drug word - U.S. Senate



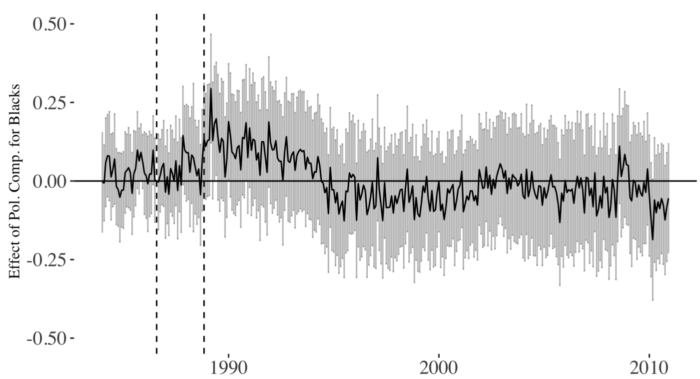
Notes: This graph shows the number of times that the word drug has been used in the Congressional speeches of the U.S. Senate from January 1984 to December 1990 over the number of speakers by party. In black we present this relative frequency for the Republican party, and in grey for the Democratic party

Figure 3.B.17: Words linked to the word drug. ALC embedding



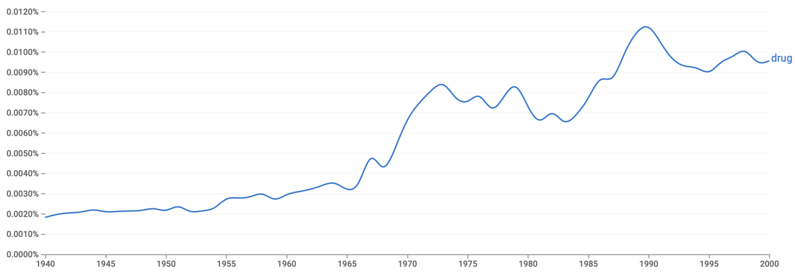
Notes: This graph shows the 20 most probable words used when talking about drug in the congressional speeches. We plot on the y axis the probability assigned to the democratic candidates and in the x axis the one assigned to the republican party. The dashed grey line is a 45 degree line.

Figure 3.B.18: Average number of crimes for possession of illicit drugs committed by Blacks



Notes: This graphs shows our dynamic treatment effect for Blacks from 1984 to nowadays.

Figure 3.B.19: Frequency of the word "drug" from Google Books Data



Notes: This graph shows the frequency of the word "drug" in Google Books data over time

Chapter 4

Traditional Media, Social Media and Local Politics in the United States

4.1 Introduction

The emergence and proliferation of social media platforms have transformed the way information is shared and consumed. However, despite this rapid increase in popularity of social media, traditional media retains its significance as a cornerstone of reliable and in-depth information dissemination (Gottfried and Shearer, 2017). Social media and traditional media are different on a number of characteristics, the most important of which is probably the audience they want to target. While there is a large literature mostly studying the demand side of social and traditional media (Snyder Jr and Strömberg, 2010; DellaVigna and Kaplan, 2007), we know less about the supply side and, in particular, about the potential interconnections between these two different technologies. Is the content produced for traditional media, such as television, mutually exclusive or is there a spillover onto social media? The first contribution of this paper is to tackle this question which, we argue, it is not trivial since a better understanding of this dimension can help clarifying the complex characteristics of the news generation process and the way it spreads to reach wider possible audiences. We exploit a shock on local television markets in the United States of America, induced by the acquisition of local TV stations by a media conglomerate, Sinclair. As already documented in the literature, these acquisitions lead to a change in the typology of content produced by these stations. We study whether the same content changes propagates on the Twitter feed of these acquired stations and we find that this is indeed the case.

Next, we investigate whether this effect is self-contained within media actors or it also affects the communication of external actors. In particular, we focus on politicians. We collect the available Twitter data of all the Representatives of the 113th Congress (2013-2014) and we study whether a change in TV content that has spillovers onto Twitter eventually also affects the communication of US representatives. The answer is not obvious. The objective function of a politician is to gain as many votes as possible and to be as visible as possible (Clinton and Enamorado, 2014; Galletta and Ash, 2022). However, the audiences of traditional media and social media are very different, making it difficult to predict their communication strategy a priori. We find that after Sinclair enters a media market, representatives from congressional districts in the media market change their online discourse by diminishing the attention devoted to local places, and suggestive evidence of increasing conservative slant.

Based on existing research (Martin and McCrain, 2019; Mastrorocco and Ornaghi, 2020), we know that Sinclair acquisitions affect content of traditional media (i.e., local television) in two ways. First, Sinclair reduces local news in favor of a national focus. Second, Sinclair—a right-leaning media group— makes content more conservative. These content changes are sharp: they are implemented within a handful of months after acquisition and become only slightly larger over time. The sharpness of these changes, and the fact that acquisitions are likely driven by business opportunities rather than being endogenous to politicians' behavior, makes this an ideal setting to investigate the dynamic effects of media content.

In this paper, we first show how the same change in content on the traditional media propagates on the social media of the TV stations. We do so by analyzing the Twitter feeds of these stations. We then focus on how politicians react to these changes in the media content. The main challenge in this case relates with measurement: answering the research questions highlighted above requires a high-frequency measure of politicians' behavior. We address this challenge by focusing on a specific group of politicians—U.S. Members of the House of Representatives—for whom we can build an innovative proxy of behavior: what they talk about in their Twitter feeds. We believe that this is a relevant proxy as, in recent years, social media have become a crucial channel for politicians to reach their electorate and express a political position (Barberá, Casas, Nagler, Egan, Bonneau, Jost and Tucker, 2019; Bessone, Campante, Ferraz and Souza, 2019). It has the additional advantage of allowing us to understand the extent to which traditional media content can spillover in the online discourse of the elites. Our empirical strategy is a differences-in-differences design using the staggered timing of Sinclair's acquisitions. Identification rests on the timing of the acquisitions being exogenous to politicians' behavior, which is an assumption likely to be satisfied in this setting. In fact, anecdotal evidence suggests that Sinclair was looking to expand over this period and took advantage of opportunities to purchase smaller broadcast group as they became available for acquisition. Event study specifications that allows the effect of Sinclair to vary in time since and to treatment help us provide suggestive evidence supporting this assumption.

First, we show that Sinclair's acquisitions impact televisions' Twitter feeds also in the precise time period that we focus on in this study, the 113th Congress (2013-2014). We do so by looking at the stations' Twitter feed. To measure content, we train an unsupervised topic model on transcripts of local TV newscasts. We then project the topics that we identify in the transcripts onto the stations' Twitter feeds. Similar to Martin and McCrain (2019), we find that after a station is acquired by Sinclair, its tweets tend to decrease coverage of local politics and increase coverage of national politics. While the previous literature just focused on the effect of Sinclair acquisitions on traditional media, we further explore this and report that the same is true as concerning the social media. Studying in deep tv station tweets, we show that there is a direct connection to the Sinclair traditional media headquarter. Indeed, the large majority of these tweets have a direct link to the original news produced on television. This confirms again that these entities behave in the same way by changing their content both online and offline.

Does this change in media content affect politicians' discourse as well? Do politicians focus their attention less to local politics and issues? To answer this question, we collect all the available Twitter handles for U.S. Representatives in the 113th Congress (2013-2014). More precisely we construct a novel measure to approximate their focus on local issues. We count the number of times each US Representative mentions a municipality from her own congressional district. We show that after Sinclair enters a media market, representatives from congressional districts in the media market change their online discourse by diminishing the attention devoted to local places. In particular, the number of mentions of municipalities decreases by 33%. The effect is already realized in the first quarter after entry, but becomes larger over time. We show that this change is not driven by some particular characteristics of the politicians such as the party affiliation or being incumbent. Moreover, there is not statistically significant difference between political campaigning period (i.e. August - November 2014) and not. For this reason, we then run a further Bert topic model of these local tweets to distinguish between tweets that are referring or sponsoring a local visit of the US Representative and tweets about local events and/or local politics (policies). We reveal that the effect is completely driven by the latter group of tweet.

Furthermore, we examine whether politicians' communication style undergoes changes in ideological slant. Following the previous literature in this field, we would expect an increase in the conservative slant driven by a Sinclair acquisition. Using the new *"A la carte"* embedding regression developed in Rodriguez, Spirling and Stewart (2021), our analysis reveals some suggestive evidence about the fact that treated U.S. Representatives exhibit more conservative features in their tweets compared to their non-treated counterparts. To do so, we select four target and divisive topics (i.e., immigration, gun, health care and taxation), we handpicked some words related to these topics and we compute cosine similarity and dot product scores assigned to these words when referring to the target ones. We observe clear patterns after a Sinclair entry. Words used more frequently by conservative (liberal) politicians experience an increase (decrease) in their similarity score for both Republicans and Democrats.We decide to focus our attention for this exercise on the immigration topic for two main reasons: first, each handpicked word presents a clear pattern, second, it was a highly divisive topic for the period.

These findings may help to increase our understanding on how media may impact not just election results (Gentzkow, Shapiro and Sinkinson, 2011; Ansolabehere, Snowberg and Snyder Jr, 2006) or voters' behaviors (Arceneaux and Johnson, 2013; Gentzkow, 2006), but also politicians way of communication.

This paper examines the influence of media content, specifically driven by Sinclair's acquisitions, on politicians' behavior and its broader implications. By analyzing changes in traditional and social media content and employing a novel measurement approach using Twitter data, we provide insights into the dynamic effects of media content on politicians' discourse and behavior. Our findings contribute to a deeper understanding of the complex interactions between media, politics, and public opinion.

4.2 Background and Literature

4.2.1 Nationalization of Local News

Local news plays a crucial role in the democratic process by providing citizens with information on the issues affecting their communities. However, the news media landscape has changed dramatically in recent years due to the rise of digital media and the decline of traditional print media (Abernathy, 2018; Pew Research Center, 2017, 2015).

While digital media has provided new opportunities for local news organizations to reach audiences, it has also created new challenges. For example, digital media has made it easier for readers to access news from sources outside their local area, which may reduce the demand for local news. Indeed, there has been a trend in the United States towards a shift in focus in local news from local issues to national politics. Scholars have identified a number of factors that have contributed to this trend other than the increase in digital media and the decline of print newspapers and the rise of digital media. Another factor that has contributed to the nationalization of local news is the growing consolidation of media ownership (Hayes and Lawless, 2018). For example, studies have shown that in markets where the Sinclair Broadcast Group (we will focus more on this particular broadcast group in the next subsection) owns stations, local news coverage is more focused on national politics and tends to be more partisan and one-sided than in comparable markets where Sinclair does not own stations (Martin and McCrain, 2019). We exploit this idea, by showing how U.S. Representatives from congressional districts where Sinclair owns stations start to talk less about local places they should represent on social networks.

Furthermore, the literature have argued that the nationalization of local news may be driven in part by the demographic changes of local communities. As cities and towns have become more diverse, local news organizations may be finding it harder to appeal to a broad audience with a shared set of interests and concerns. This may be leading them to focus more on national politics, which can generate higher levels of interest and engagement than local issues (Boczkowski and Mitchelstein, 2013).

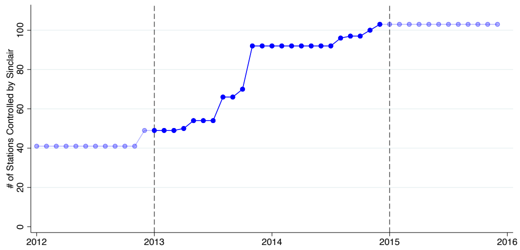
However, the trend towards a focus on national politics in local news has raised concerns about the impact on democracy and civic engagement at the local level (Commission et al., 2011). As local news organizations have shifted their focus away from local issues, there are fears that citizens may be less informed about the issues that affect their daily lives and less engaged in local politics (Hendrickson, 2019). Moskowitz (2021) suggests that without access to reliable local news sources, voters are more likely to rely on national news sources for information about local candidates and issues. This can result in a nationalization of local elections, with voters making decisions based on national issues and party affiliation rather than local concerns. This argues that this trend has the potential to undermine the connection between local voters and their elected representatives, as well as the ability of local communities to address their unique challenges and needs. With this paper we want to shed more light on this, by studying how individuals respond after a decline in attention from their direct politicians to the local places they should represent.

4.2.2 Sinclair Broadcast Group

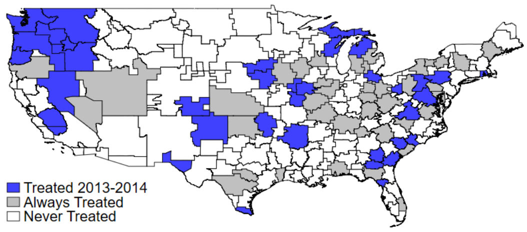
Since 2010, the local TV market in the United States has seen a stark increase in ownership concentration, primarily explained by the emergence of large broadcast groups owning a significant share of local TV stations (Matsa, 2017). We focus on one of the most active players in the local TV market: the Sinclair Broadcast Group. Sinclair went from owning 33 stations in January 2010 to 117 in December 2017. In this paper we focus on a very specific period of Sinclair acquisitions: 2013-2014. As Figure 4.2.1(a) shows, Sinclair went from owning 40 stations in January 2013 to 103 in December 2014. This corresponds to about 75% of all the acquisitions of the broadcast group from 2010 to 2017. Acquisitions have taken place in media markets across the country (Figure 4.2.1(b)), although Sinclair was particularly active in medium-sized media markets.

As the literature already showed in previous research papers, Sinclair, compared to the other broadcast groups, hold a right-leaning political orientation and appears to

Figure 4.2.1: Sinclair Ownership over Time and Space



(a) *Number of Stations Controlled by Sinclair*



(b) *Media Market Experiencing Sinclair Entry*

Notes: Panel (a) shows the number of stations controlled by Sinclair in each month from January 2010 to December 2017. We highlight the period going from January 2013 to December 2014, our period of interest. Panel (b) shows year of Sinclair entry across media markets in the United States. In blue are media markets that are acquired between 2013-2014. Never treated are media markets that never experience Sinclair entry in our period of interest; always treated are media markets that have at least one station controlled by Sinclair at the beginning of the period of interest (January 2013).

be particularly interested in controlling the messaging of its stations (Miho, 2020; Mastrorocco and Ornaghi, 2020). More relevant, for the purpose of this work, it is the work Martin and McCrain (2019) showing how after a Sinclair's acquisition, the ideological slant of the acquired stations moved to the right and the new ownership increases national coverage, mostly at the expense of local stories.

4.2.3 Social Network and Politicians

Social networks have become an increasingly important tool for politicians to communicate with their constituents and to promote their policies and ideas (Hampton, Rainie, Lu, Shin and Purcell, 2015). In particular, Twitter has emerged as a powerful platform for politicians to engage with voters and to shape public opinion. This is especially true in the United States, where a large percentage of elected officials have Twitter accounts today.

Twitter was launched on March 21, 2006, and became publicly available on July 15, 2006. Three years after the platform was launched, Twitter had 6 million registered users. By December 2011, this number had grown to 100 million registered users, and by December 2013, Twitter had over 232 million active users worldwide.

As regarding politicians, in 2009, only 5% of US Representatives had a Twitter account. By 2014, this number had increased to 95%, and as of 2021, all members of Congress have a Twitter account (Barberá et al., 2019). The number of tweets sent by US Representatives has also increased significantly over time.

The rise of Twitter as a political tool can be attributed to a number of factors (Larsson and Moe, 2012). First, Twitter allows politicians to bypass traditional media gatekeepers and speak directly to their constituents (Enli and Skogerbø, 2013). This is particularly important in an era where trust in the media is declining and where politicians are looking for alternative ways to reach voters. Second, Twitter allows politicians to reach a wider audience than they could through traditional campaign methods (Hargittai and Litt, 2011). Third, Twitter provides politicians with real-time feedback on their policies and ideas. By monitoring the conversation on Twitter, politicians can quickly assess public opinion and adjust their messaging accordingly.

4.3 Data

For this project, we combine different data sources. The main analysis is run at the congressional district year-month level, while, when analysing the TV station Twitter content we work at the TV station year-month level.

Station Data: The initial dataset on local TV station comprises a comprehensive selection of 835 full-powered commercial TV stations affiliated with major networks, namely ABC, CBS, FOX, and NBC. This valuable information on the served markets and yearly network affiliations is obtained from BIA-Kelsey, an esteemed advisory firm specialized in the media industry.

Sinclair Acquisitions: For the analysis of Sinclair control over stations, we gather pertinent data from the annual reports shared with shareholders by the Sinclair Broadcast Group. This data includes crucial details on the dates when Sinclair assumed control over the station's programming. In instances where the annual reports do not provide exact takeover dates, we rely on the BIA/Kelsey data, which offers a comprehensive transaction history for all stations in our sample. The criterion used for identifying stations under Sinclair's control encompasses those owned and operated by the Sinclair Broadcast Group, Cunningham Broadcasting, or stations under Sinclair's programming control through local marketing agreements. The period under consideration for Sinclair acquisitions is from 2013 to 2014, during which notable acquisitions occurred in August 2013, November 2013, and August 2014.

Geographical data: To enrich our analysis, we utilize U.S. congressional district and media market shapefiles from IPUMS USA, a reliable repository of harmonized U.S. census microdata. These datasets are integrated to allocate each congressional district (CD) to the corresponding media market (DMA) based on geographical borders. Additionally, we incorporate U.S. Census Grids[1] data from the Socioeconomic Data and

[1]The U.S. Census Grids (Summary File 1), 2000 data set contains grids of demographic and socioeconomic data from the year 2000 U.S. Census in ASCII and geotiff formats. The grids have a resolution of 30 arc-seconds (0.0083 decimal degrees), or approximately 1 square km. The gridded variables are based on census block geography from Census 2000 TIGER/Line Files and census

Applications Center (SEDAC), a dataset produced by Columbia University's Center for International Earth Science Information Network (CIESIN). This data contains essential demographic and socioeconomic information from the year 2000 U.S. Census, providing valuable insights at a 30 arc-seconds resolution (approximately 1 square km). These geographical datasets play a crucial role in constructing our treatment variable, specifically assessing the population residing within a Congressional District that falls under a particular media market. Detailed information on the treatment assignment based on population is explicated in the subsequent section.

Newscast Transcripts: To delve into the impact of Sinclair acquisitions on content, we extract local TV newscast transcripts from ShadowTV, a reputable media monitoring company. Each station's dataset encompasses closed caption transcripts of evening newscasts (broadcasted from 5 pm to 9 pm) for a randomly chosen day each week. This dataset covers 325 stations (approximately 39% of the sample) across 113 media markets during the period 2013-2014. Utilizing an automated procedure grounded in content similarity, we segment each transcript into distinct stories, following the approach outlined by Mastrorocco and Ornaghi (2020). To identify the topics covered by local TV stations in their newscasts, we implement a Latent Dirichlet Allocation (LDA) topic model with 15 topics. Prior to training the LDA model, we undertake standard pre-processing and text normalization techniques, such as punctuation removal, elimination of stop-words, and stemming, as detailed in the work Ash and Hansen (2023).

Stations' Activity on Twitter: For a comprehensive analysis of the station's online content, we manually compile Twitter handles for 698 stations active on Twitter from 2013 to 2014. To gather relevant data, we employ the Twitter Developer Academic Research API, enabling us to collect each station's tweets along with associated metrics, including likes, replies, and retweets, from 2013 to 2014. We use the stations' tweets to document the effect of acquisitions on the station's online content. To do so, we project the LDA model that we trained on the transcripts data on the normalized corpus of the TV stations' tweets. In Figure 4.B.1, we report the 10 most used bigrams for the two main topics of interest: national and local politics.

U.S. Representatives' Activity on Twitter: To gather data on U.S. representatives' Twitter activity, we obtained their Twitter handles from Votesmart and the Congress.gov website. We completed our dataset by manually searching for the accounts on the Twitter website. Utilizing the Twitter Developer Academic Research API, we collected the text of each representative's tweets along with their corresponding metrics such as likes, replies, and retweets. This data collection spanned from 2011 to 2014. Out of the total 435 congresspeople presented in the House of the Represen-

variables (population, households, and housing variables).

tatives in the 113th Congress, 401 had active Twitter accounts during the period of 2013-2014. However, only 370 representatives were found to be actively tweeting during this time frame.[2]. By excluding the U.S. territories and the states of Alaska, Hawaii, and DC, we were left with 367 active representatives on Twitter for our analysis. To enhance the balance of our sample, we further focused on representatives who tweeted in at least 12 separate months during 2013-2014 and who tweeted at least once in the first three months of our sample (pre-treatment period)

We utilized representatives' tweets to quantify the level of attention devoted to local topics and to compute the conservative slant. We proxy local attention in three ways:

- For each Congressional District we identify the municipalities inside the borders of the CD. We then count the number of times that municipalities belonging to the representative's congressional district are mentioned by the representative in her tweets by searching and counting in the text the presence of these places (i.e., using regular expression technique). We, then, winsorize our outcome variable at the 5th and 95th percentiles to minimize the influence of outliers. In particular, we do this to avoid the results being driven by some specific tweets or data errors[3]. We transform this variable using a inverse hyperbolic sine (IHS) transformation. We, then, run a Poisson estimation as a robustness check[4].

- Using the same variable we identify a dummy variable for identifying month with at least one tweet about local constituencies.

- Following the previous construction and procedure, we count the number of times that "local bigrams" (namely, "city hall", "city council", "city meeting", "town hall", "city mayor")[5] are mentioned by the representative. We then create a dummy variable for identifying month with at least one tweet using one of these very specific bigram.

Once identified the local tweets of a politicians (the one mentioning a municipalities within their congressional district), we run a Bert topic model of these documents to distinguish between tweets related to a local visit of the US Representatives and tweets about local policies, events or institutions. We present the results of this topic model in Figure 4.B.2.

[2]Some congresspeople is present on Twitter, but they don't have any tweet, so they are not active.

[3]In appendix we show that our results remain unchanged when we winsorize more at the 10th and 90th percentiles or at the 1st and 99th percentiles.

[4]In the robustness sections we use also other different transformation methods using the log transformations

[5]We identify these bigrams following Martin and McCrain (2019) and the results of our topic model in Figure 4.B.1.

We then pass in measuring the conservative slant. To do so we use the new *A la carté* embedding regression method suggested in Rodriguez, Spirling and Stewart (2021). We focus on some target words specifically of important US policies issues (i.e., immigration, gun rights, health care, abortion, taxation) and we identify the words closest to each target word (using cosine similarity and the dot product scores). We then distinguish between Republicans and Democrats and we compare a pre-treatment period to a post-treatment period to see if these scores evolve and/or change after a Sinclair acquisition.

Congressional Speeches: One would expect that a change in the way a politician communicates on a social network may affect also the way the same politician speaks. For this reason we collect congressional speeches for the period taken into consideration and we construct a measure of local attention. We proxy local attention in a different way. We count the number of time a US Representative mentions the state of her constituency in each congressional speech. We can't count the number of local places because we found out that usually politicians in the congressional speeches don't tend to talk specifically about their constituencies.

4.3.1 Descriptive Statistics

In Table 3.A.1 we present the descriptive statistics of the main variables used in the paper. We present number of observations, mean, standard deviation, minimum and maximum value for each variables

4.4 Effect of Sinclair Acquisitions on TV Stations' Tweets

4.4.1 Specification

The first step of this paper is to show that Sinclair acquisitions may impact the online content of the TV stations as well.

To do so we begin by exploring how Sinclair acquisitions impact the content of the station's tweets using a differences-in-differences design. For this part of the analysis we work with data at the TV station year-month level. The specification we implement is:

$$Topic_{st} = \beta Sinclair_{st} + \delta_s + \delta_t + \epsilon_{st} \tag{4.1}$$

where $Topic_{st}$ is the weight of the national or local politics topic assigned by the topic model across all tweets of station s in month t; $Sinclair_{st}$ is an indicator variable equal to one after the station s is acquired by Sinclair at year-month t; δ_s are station fixed effects; and δ_t are year-month fixed effects. We cluster the standard errors at the media market level. We then provide evidence supporting the parallel trends assumption by estimating an event study version of Equation 4.1. In particular, we estimate the following specification:

$$Topic_{st} = \sum_{\tau=-q}^{-2} \gamma_\tau Sinclair_{s,\tau} + \sum_{\tau=0}^{m} \delta_\tau Sinclair_{s,\tau} + \delta_s + \tag{4.2}$$

where $Topic_{st}$ is the average weight for the national or local politics topic[6] across all tweets of station s in month t. We include q leads or anticipatory effects and m lags or post-treatment effects (omitting $t-1$ period). δ_s and δ_t are station and time fixed effects. We omit the event time dummy at $t = -1$, implying that the event time coefficients measure the impact of Sinclair acquisition relative to the month just before the occurrence.

4.4.2 Results

In Table 4.4.1 we confirm the results found in Martin and McCrain (2019), but using Twitter data. After Sinclair acquires a station, the share of the local politics topic decreases by 1.72 percentage points. The effect is significant at the 5% level, and corresponds to 9.5% of the baseline mean. This decline is compensated by an increase in coverage of national politics: the share of the national politics topic increases by 1.69 percentage points. This is significant at the 5% level and represents a large increase (around 13%) relative to the baseline mean.

We then show in Figure 4.2.1 the results of the event study specification proposed in Equation 4.2 using the machinery implemented by Borusyak, Jaravel and Spiess (2021). From both plots it is possible to note that in the months leading up a Sinclair acquisition there was not statistically significant difference between acquired and not acquired TV stations in their way of tweeting about local and national topics. After the acquisition there is a quite fast change in their way of communication through the social network. Indeed, in treated TV stations the local topic become less important than in the the not treated ones after the acquisition. The local topics decreases its importance in the month immediately after the Sinclair entry, and then this fall stays constant over time, at least for the first year after the acquisition. The same is not true

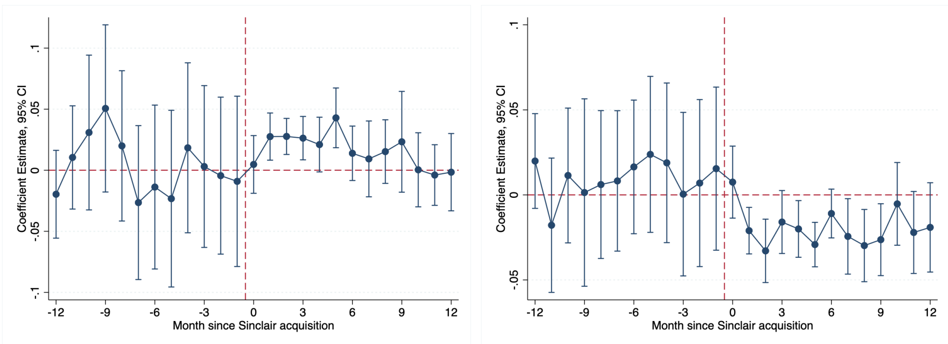
[6] Identified using an LDA topic model first trained on TV station transcripts on the TV stations Twitter feeds. In Figure 4.B.1 we report the most used bigrams related to the local and national topic[7]. Our results are very similar to the ones identified in Martin and McCrain (2019).

Table 4.4.1: Effect of Sinclair Acquisitions on Topics of TV Stations' Tweets

	(1) National Politics	(2) Local Politics
Sinclair	0.0172**	-0.0169**
	(0.0085)	(0.0058)
Month FE	Yes	Yes
Station FE	Yes	Yes
Observations	12,465	12,465
Mean Dep. Variable	0.1800	0.1320

Notes: This table shows estimates of Equation 4.1 for the national and local topics derived from our trained LDA topic model. The regressor of interest is a dummy variable taking value 1 when a TV station is acquired by Sinclair. We reports a specification with year-month fixed effects and station fixed effects. Standard errors are clustered at the media market level. *p<0.1; **p<0.05; ***p<0.01

Figure 4.4.1: Effect of Sinclair Acquisitions on Topics of TV Stations' Tweets - Event Study



(a) *National Topic* **(b)** *Local Topic*

Notes: This graph shows dynamic treatment effect estimates of the effect of Sinclair acquisition on the probability to tweet about national (Panel (a)) and local (Panel (b)) topic. The dashed red vertical lines indicate the timing of the acquisition. The dashed red horizontal line shows 95% confidence intervals for standard errors clustered at the media market level.

as concerning the national topic. Indeed, the attention devoted to this topic increases in the month immediately after the acquisition and this increase stay constant at least for the first 6 months after acquisition.

After having showed this, we analyze more descriptively the TV stations Twitter activity. When using a social network, a traditional media account may have two different behaviors: creating new piece of news and reporting them on the social media; or reporting directly the same news they showed on the traditional media. If this second option would be the case, we could easily state that the behavior of an acquired TV station is the same both in the traditional and social media. This would mean that our previous result exactly confirms the findings from Martin and McCrain (2019), but that also results on the conservative slant would be confirmed.

To do so we analyze how many tweets of the TV stations have an URL link to another website. We found that in the more than 11 millions tweets of the TV stations, almost 80% have an URL link. We then transform the shorten Twitter URL[8] into the real website URL. After this first step, we then study the URL link to understand that it is a link to a TV station (or name of a show of the TV station) web-page. We do so by searching in the URL for the name of the TV station (call sign) or the name of the shows of the TV station.

We see that of these URL, 80% are direct link to the TV station or to the TV shows of the TV stations. The remaining 20% are link to other social networks (such as Youtube and Facebook), to weather forecast webpages, to national news (i.e., Fox News) or to deleted links.

This descriptive evidence is reassuring since it showing us that when using Twitter the TV stations usually just write a short headlines of a news and then they report their own news (the same one they reported previously in the traditional media). Having show this we can confirm that after a Sinclair entry, these treated TV stations change their way of communication on the social networks as well compared to the not treated ones. This in particular reduces the attention given to local politics, increasing the one delivered to national politics and increases the conservative slant. In the next part of the paper we will study if the same happens in the social network in general, we will focus our attention on a particular character: the US Representatives.

4.5 Effect of Sinclair Acquisitions on Politicians' Tweets

4.5.1 Local Politics coverage

Specification

Our empirical strategy is a differences-in-differences design exploiting the staggered timing of Sinclair's acquisition of local TV stations as a shock to the media content that each representative is exposed to. Congressional districts and media markets follow different geographies: media markets are generally collections of counties, while congressional districts often cut through counties especially due to gerrymandering.

[8]Twitter has its own shorter link. All links shared on Twitter, including links shared in Direct Messages, are automatically processed and shortened. This is done to allow the user to share long URLs in a tweet while maintaining the maximum number of characters for a message; as a quality signal in determining how relevant and interesting each tweet is when compared to similar tweets; to protect users from malicious sites that engage in spreading malware, phishing attacks, and other harmful activity.

As a result, it is not necessarily straightforward to match each congressional district (CD) to the media market (DMA) that covers it. In this paper, we get around this issue by assigning a DMA to a CD based on the population of the CD that DMA contains. Basically, if a specific CD contains more than one DMA, we weight the DMA by the population of the CD that it contains. We categorize a congressional district as treated when a TV station is acquired within a designated market area that encompasses at least 5% of the congressional district's population ((Snyder Jr and Strömberg, 2010; Balles, Matter and Stutzer, 2022). Our sample includes three types of units (congressional districts): "always treated" (units treated prior to January 2013), "treated" during the 2013-2014 period, and "never treated". Since we have heterogeneity in time in our treatment, but our units are not treated multiple times in the period considered, we use as main estimator the one proposed in Borusyak, Jaravel and Spiess (2021). The baseline specification that we estimate is:

$$y_{it} = \beta_1 Sinclair_{d(i)t} + \delta_i + \delta_t + \delta_{s,t} + \epsilon_{it} \tag{4.3}$$

where y_{it} is our measure for attention dedicated to local places for representative in CD i at month t; $Sinclair_{d(i)t}$ is an indicator variable equal to one after Sinclair enters the media market that covers the congressional district i; δ_i are congressional district fixed effects; δ_t are year-month fixed effects, and finally we control for state by year-month fixed effects $\delta_{s,t}$ for taking into account any effects of unobserved time-varying characteristics of the states that may be correlated with our outcome variable. To ensure that representatives that are more active on Twitter drive the effects we estimate, we weight the regression by the number of tweets of the US representative over the January to March 2013 period (before the treatment). Standard errors are clustered at the congressional district level. In others estimations we include State linear time trends, we also control for some baseline characteristics interacted with year fixed effects. In particular, the population of the congressional district based on the 2010 U.S. census data, and the number of places (municipalities that a politician may or may not mention in her/his tweet) in each congressional district.

We then estimate event study specifications in which the treatment effect varies in time since/to Sinclair entry, both as a way to support the parallel trends assumption and to understand the evolution of the treatment effect over time [9].

$$y_{it} = \sum_{\tau=-q}^{-2} \gamma_\tau Sinclair_{d(i),\tau} + \sum_{\tau=0}^{m} \delta_\tau Sinclair_{d(i),\tau} + \delta_i + \delta_t + \delta_{s,t} + \epsilon_{it} \tag{4.4}$$

[9] We implement the event-study designs using estimators robust to heterogeneous effects in two-way fixed effects designs proposed by Borusyak, Jaravel and Spiess (2021).

where y_{it} is our measures for the attention to local places across all tweets of representative of congressional district i in month t. We include q leads or anticipatory effects and m lags or post-treatment effects (omitting $t-1$ period). δ_i and δ_t are CD and time fixed effects. Finally, also in this case we introduce state by year-month fixed effects. We omit the event time dummy at $t = -1$, implying that the event time coefficients measure the impact of Sinclair acquisition relative to the month just before the occurrence.

Main Results

We present the results of our study based on Equation 4.3 in Table 4.5.1, which shows the effect of Sinclair's entry on the number of times a local place is mentioned in a representative's Twitter feed. To account for the numerous zeros in our dataset, we transform the counting variable using an inverse hyperbolic since transformation[10]. Panel A of the table reports difference-in-differences (DiD) estimates for different specifications using the two-way fixed effects (TWFE) estimator, while in Panel B we report the DiD estimation for the same specifications using Borusyak, Jaravel and Spiess (2021) estimator, to verify the robustness of our estimations to the heterogeneity in timing of our treatment.

Our study reveals that Sinclair's entry into the media market of a representative's jurisdiction causes a significant decrease of almost 33% in the number of mentions of municipalities in our preferred specification (column 3). This effect is statistically significant at the 5% level, using both the Borusyak, Jaravel and Spiess (2021) estimator and the standard TWFE. We find the result to be robust in all the more rigorous specifications, including different fixed effects, linear and dynamic state trends. To control for confounding variables, we include the population of the district interacted by year fixed effects in column 4, and the number of places presented in a congressional district interacted with year fixed effects in column 5.

After a Sinclair entry the US Representatives from a treated congressional district devotes less attention to their local constituencies. One could expect a reaction from their electorate which may be less interested in what these politicians produce online. For this reason in Table 4.A.3 we report estimates for the effect of Sinclair entry on politicians' Twitter metrics. We use four different outcome variables: inverse hyperbolic transformation for the number of tweets, the share of likes, replies and retweets over the total number of tweets. We use the most rigorous specification controlling for year-month and congressional district fixed effects, state by month fixed effects and including the population district and the number of places present in a congressional district

[10] We also show results using a dummy variable taking value 1 when a congressperson talk at least once in her tweets about her local constituency.

Table 4.5.1: Effect of Sinclair Entry on Place Mentions in Politicians' Tweets

	Ihs Place Mentions				
	(1)	(2)	(3)	(4)	(5)
	Panel A: TWFE				
Sinclair	-0.1556	-0.1869*	-0.3343**	-0.3281**	-0.3322**
	(0.1480)	(0.0972)	(0.1498)	(0.1480)	(0.1464)
	Panel B: BJS				
Sinclair	-0.1067	-0.1394*	-0.2376**	-0.2256**	-0.2162*
	(0.0923)	(0.0846)	(0.1132)	(0.1107)	(0.1107)
Mean Dep. Variable	1.3623	1.3623	1.3623	1.3623	1.3623
Observations	8,016	8,016	7,992	7,992	7,992
Clusters (Representatives)	334	334	334	334	334
Month FE	Yes	Yes	Yes	Yes	Yes
MOC FE	Yes	Yes	Yes	Yes	Yes
State Time Trends	No	Yes	No	No	No
State by Month FE	No	No	Yes	Yes	Yes
Population District x Year FE	No	No	No	Yes	Yes
Number Places in CD x Year FE	No	No	No	No	Yes

Notes: This table shows estimates of Equation 4.3 which shows the effect of Sinclair's entry on the number of times a local place is mentioned in a representative's Twitter feed. We apply an inverse hyperbolic transformation to the outcome variable and we winsorize it at 5%. Panel A shows TWFE estimates, while Panel B shows Borusyak et al. (2021) estimates. The regressor of interest is an indicator variable equal to one after Sinclair enters the media market that covers the congressional district. Different columns report different specifications of Equation 4.3. Column 1 reports a specification with district and month by year fixed effects. In column 2 we add state specific linear time trends. In Column 3 we control for state by year-month fixed effects and in Column 4 we control for the population interacted by year fixed effects. In column 5 we add also the number of places present in a CD interacted with year fixed effects as control. Standard errors are clustered at the congressional district level. *p<0.1; **p<0.05; ***p<0.01

interacted by year fixed effects. These estimates show that there is not an effect on these metrics. Indeed, after a Sinclair entry, even if the treated US Representatives change their way of communication on Twitter by referring less about their local constituencies, the metrics are not impacted by this change in their behavior.

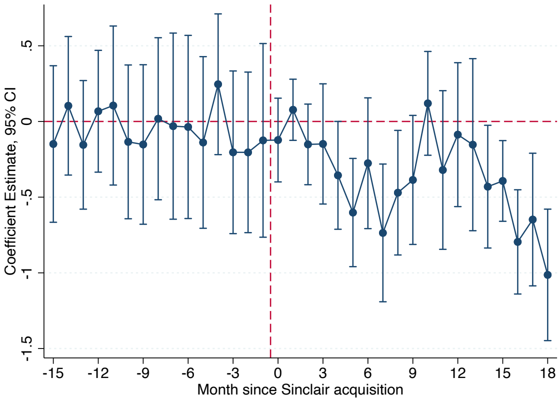
We then provide supportive evidence for the parallel trends assumption in Figure 4.5.1, which uses the Borusyak, Jaravel and Spiess (2021) estimator: pre-trends coefficients are flat leading up Sinclair's entry. We also observe that there is a negative effect on the attention that representatives devote to local topics in the period immediately following the acquisition (in particular after 3 months). The effect seems to be even stronger in the long run (after almost one year). This is not so surprising, indeed we would have expected a period of adaptation between the change in the traditional media ownership and the politicians behavior. In Figure 4.B.3 and Figure 4.B.4 we show the same event studies, using the TWFE estimator at the month level and aggregating the coefficients by quarter. The results are similar to our main event study. The parallel trends assumption is satisfied and the effect is stronger after one year. This evidence suggests that politicians adapt to the change as well, but they need more time compared to the TV stations which changed their behavior in the communication faster.

In Figure 4.5.2, we show the same event study specifications for our intensive margin variable and for a further dummy variable taking value 1 if in the month the U.S. representative tweets using at least one local politics bigram (local slant) identified by the topic model run on the TV station transcripts. We present the these event studies using the Borusyak, Jaravel and Spiess (2021) estimator confirming our previous findings. Indeed, pre-trends coefficients are flat leading up Sinclair's entry, and after the entry there is a negative effect on the probability to tweet using local places or local slant. The pattern is very similar to the one identified for our main outcome variable. In appendix Figure 4.B.5 reports the same event studies but using the TWFE estimator.

In Table 4.A.5 we present that our results hold even when accounting for different winsor transformations, count model and using a dummy as outcome variable. We, also implement the Poisson pseudo-maximum likelihood regressions (PPML) with multi-way fixed effects, as described by Correia, Guimarães and Zylkin (2019*a*), for verifying that our count models don't bias our results (column 9). The estimator employed is robust to statistical separation and convergence issues, due to the procedures developed in Correia, Guimarães and Zylkin (2019*b*).

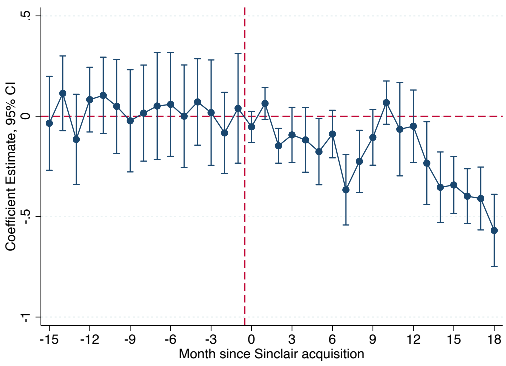
In Table 4.A.5 we present the estimations of our most rigorous specification, which includes year-month, congressional district, state by month fixed effects, and the interaction of the number of places present in a CD and the population of the congressional

Figure 4.5.1: Effect of Sinclair Entry on Place Mentions in Politicians' Tweets, Event Study (BJS)

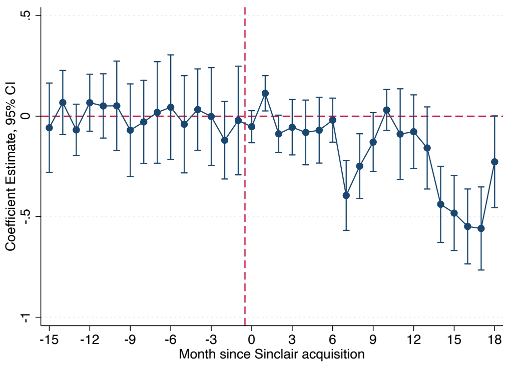


Notes: This graph shows dynamic treatment effect estimates of the effect of Sinclair acquisition on our main outcome variable: the inverse hyperbolic sine transformation of the count of local places by month on congresspeople tweets. The dashed red vertical lines indicate the timing of the acquisition. The dashed red horizontal line shows 95% confidence intervals for standard errors clustered at the congressional district level. The plot is constructed using the machinery suggested by Borusyak, Jaravel and Spiess (2021)

Figure 4.5.2: Effect of Sinclair Entry on Place Mentions in Politicians' Tweets, Event Study (BJS)



(a) *Dummy Place Mentioned*



(b) *Dummy Local Slant*

Notes: This graph shows dynamic treatment effect estimates of the effect of Sinclair acquisition on a dummy taking value one if in a given month a congressperson tweeted at least once about a local place (Panel (a)) and using a local bigram (Panel (b)). The dashed red vertical lines indicate the timing of the acquisition. The dashed red horizontal line shows 95% confidence intervals for standard errors clustered at the congressional district level. The plots are constructed using the machinery suggested by Borusyak, Jaravel and Spiess (2021) by year fixed effects. Panel A presents the results using the TWFE estimators, while we use the Borusyak, Jaravel and Spiess (2021) estimator in panel B. We use as outcome variables: the one used in Table 4.5.1 (column 1); a dummy variable taking value 1 if in the month the US representative tweets about a local constituencies of her district (column 2); the log transformation of the number of mentions (column 3); the log +0.1 transformation of the number of mentions (column 4); the log + 1 transformation of the number of mentions (column 5); the inverse hyperbolic sine transformation of the number of mentions winsorized at 1% (column 6) and winsorized at 10% (column 7); and finally in column 8 we present the Poisson estimator. The results are negative and statistically significant at the 5% of the exception of the log transformation.

We then study if these effects are driven by some particular characteristics of the US Representatives. We do so by running some heterogeneity by the party of the politician, if the US Representative was present or not in the previous congressional period and verifying if tweeting during the political campaigning period change the results.

We present these heterogeneity in Figure 4.B.7. We run our most rigorous specification and we interact our treatment variable by three different dummy variables: the first taking value 1 if the US Representative is a member of the Republican party and 0 otherwise; the second taking value 1 if the US Representative was present in the House of the Representatives in the previous congressional period; and the third one taking value 1 in the political campaigning period (from August to November 2014). From these heterogeneities we can see that there is never a statistically significant difference, meaning that these characteristics seem not to explain our results. In the next subsection we are going to further analyse some characteristics as possible mechanism behind our results.

We also check if the decrease in attention devolved to local constituencies is reflected in the congressional speeches as well. We first run the same search model and we discovered that in general (even before a Sinclair acquisition) the US Representatives very rarely talk about a specific local municipality in the official congressional speeches. We decide to proxy the local attention by counting the number of times a US Representative mentions her state in the congressional speeches. Studying congressional speeches has two disadvantages: first it is a less frequent measure since not every month we have an observation for each politician; secondly the length of these text data.

We report the result of this analysis in Table 4.A.4. This table follow the construction of Table 4.5.1 where the different columns represent different specification. From the table we can see that the results follow the ones of the social media. We see that treated congresspeople refer almost 15% less to their state after a Sinclair acquisition compared to not treated ones. This result is significant at the 10% even when running the most rigorous specification controlling for year-month, congressional district, state by year-month fixed effects and including the population of the congressional district and the number of places in a CD interacted by year fixed effects. This result is suggestive that a Sinclair acquisition may change the political language not just online but also offline.

4.5.2 Mechanism

We showed so far that after a Sinclair entry the treated US Representatives start to devote less attention to their local constituencies. We showed that this effect is not driven by some specific characteristics of the politicians. For this reason in this subsection we try to investigate more the tweets about a local place. For doing this we run a BERTopic model (Grootendorst, 2022) using the tweets about a local place as corpus. We identified 33 topics (in Figure 4.B.2 we report the first 20 with the highest importance). We define as topic about a local meeting or visit of the US Representative in the local place “topic -1" and “topic 0". We do this by analyzing the words with the highest weight in each topic, and by using the BERTopic search engine for topics using specific terms. After having trained the model, we can search for topics that are similar to a specific word. We did this by searching for specific words "meeting" and "visit". The model identified topics -1 and 0 as the ones with the highest similarity score for these two words. After having establish this we divide the tweets about a local places between tweets about a local visit and tweets not about a local visit (all tweets about local events, episodes, policies or politics). We finally run our most rigorous specification using these two category of tweets as outcome variables.

We report these results in Table 4.5.2. In panel A we report TWFE estimations and in panel B the Borusyak, Jaravel and Spiess (2021) ones. In column 1 we use as outcome variable the inverse hyperbolic sine transformation of the number of tweets about a local place created by a US Representative in each month; while in column 2 we focus on those tweets about a local place but not about a visit and in column 3 the tweets about a local visit. From this table is clear that our results are completely driven by those local tweets that are not talking about a local visit. These are tweets talking about local episodes (i.e., crime, weather) or local politics/policies (i.e., local elections, specific policies such as immigration policies) or about local institutions (i.e., fire and police departments).

In Table 4.A.6 we run the same estimations but using as outcome variables dummy taking value 1 when in a given month the US Representative tweets about a local place and respectively a local visit or not. The results are in line with the previous one. Finally, we run a further heterogeneity for understanding if this result may be explained by the

Table 4.5.2: Effect of Sinclair Entry on Nr of Tweets about Local Places

	Ihs Nr Tweets Local Places		
	All	No Visits	Visits
	(1)	(2)	(3)
	Panel A: TWFE		
Sinclair	-0.2964**	-0.3068**	-0.0091
	(0.1490)	(0.1420)	(0.1020)
	Panel B: BJS		
Sinclair	-0.2077*	-0.3770*	-0.3370
	(0.1123)	(0.1947)	(0.2537)
Mean Dep. Variable	1.3365	1.2130	0.3814
Observations	7,992	7,992	7,992
Clusters (Representatives)	334	334	334
Month FE	Yes	Yes	Yes
MOC FE	Yes	Yes	Yes
State by Month FE	Yes	Yes	Yes
Population District x Year FE	Yes	Yes	Yes
Number Places in CD x Year FE	Yes	Yes	Yes

Notes: This table shows estimates of Equation 4.3 which shows the effect of Sinclair's entry on the number of tweets about a local place in the US Representatives Twitter feed. Each column represent a different outcome variable. In column we have the total count of tweets about a local place. In column 2 we have the total number of tweets about a local not identified by a local visit; while in column we have thte total number of tweets about a local place identified with a visit. We apply an inverse hyperbolic transformation to the outcome variable and we winsorize it at 5%. Panel A shows TWFE estimates, while Panel B shows Borusyak et al. (2021) estimates. The regressor of interest is an indicator variable equal to one after Sinclair enters the media market that covers the congressional district. We report the most rigourous specification including district and month by year fixed effects and state by year-month fixed effects. We also control for the population interacted by year fixed effects and the number of places present in a CD interacted with year fixed effects as control. Standard errors are clustered at the congressional district level. *p<0.1; **p<0.05; ***p<0.01

political campaigning period or not. We report the estimates for this heterogeneity in Table 4.A.7. The estimates reveal that our results is completely driven by a decrease in the local tweets about not local visits in not political campaigning period. Indeed, during the political campaigning we don't find any statistically significant results and moreover the coefficients are positive. In Figure 4.B.6 we run event studies using as outcome variable the inverse hyperbolic sine transformation of the number of tweets about a local politics (i.e., not about a local visit) on a given month and using the dummy variable as well. From the plots we can see that these trends mirror exactly the decrease in the mention of the local places we showed previously.

Finally, we aim to establish a further connection between the social media behavior of TV stations and US Representatives. Specifically, we investigate whether TV stations tweet less about US Representatives after a Sinclair entry. The intuition behind this check is that the US Representatives are considered local politicians since they represent some specific local constituencies within a congressional district. To gauge this relationship, we constructed an outcome variable by searching for the surnames of US Representatives from the same US state as the TV station, along with specific words related to congresspeople, such as "congressperson," "congresswoman," "congressman," "rep," and "representative," in the tweets of each TV station. If a tweet meets these criteria, we interpret it as a mention of a US Representative. The results are presented in Table 4.A.8. We utilized three estimation strategies: TWFE estimator in the first two columns, the Poisson model in columns 3 and 4, and the Borusyak, Jaravel and Spiess (2021) machinery in columns 5 and 6. For each strategy, we incorporated first year-month and TV station fixed effects, and subsequently, we added DMA by year-month fixed effects. The table reveals a negative relationship between Sinclair entry and the probability of mentioning a US Representative. Notably, this effect is statistically significant at the 10% level when using the Poisson estimator. We interpret this evidence as suggestive of a decreasing attention to local politics following a Sinclair entry.

4.5.3 Conservative Slant

We find, so far, that following Sinclair's acquisition, the TV stations that were acquired experience a reduction in their local news coverage both on television and on their social media channels. As a result, politicians appear to respond to this change in content by diminishing their attention to and mentions of the local places they represent in their tweets. We know, from previous literature (Martin and McCrain, 2019) that Sinclair has an effect also on the slant of the news, making them more conservative. Thus, we investigate whether politicians from treated congressional districts align their discourse with this conservative shift using the Twitter feeds as our data source.

To find a direct measure for the conservative slant is not straightforward. To examine this, we employ the innovative *"A la carte"* (ALC) embedding regression method developed by Rodriguez, Spirling and Stewart (2021) [11]. This approach utilizes pre-trained embeddings from a collection of texts, specifically the speeches made by politicians in House of the Representatives. These embeddings are combined with a small set of sample instances that demonstrate the usage of a focal word. By doing so, a new embedding that is tailored to the specific context of the word is generated. This process involves a simple linear transformation of the averaged embeddings for words within the context of the focal word.

In our analysis, we select four focal words that are related to important political issues during the period of study: *immigration, gun, health care and taxation.* We regress on the first dimension of the NOMINATE score (Poole and Rosenthal, 1985) [12]. This regression approximates a sequence of separate embeddings for each politician, approximated using a line in the NOMINATE space. We, hence, estimate this regression following the same procedure suggested by Rodriguez, Spirling and Stewart (2021):

$$Y = \beta_0 + \beta_1 Nominate + \epsilon \tag{4.5}$$

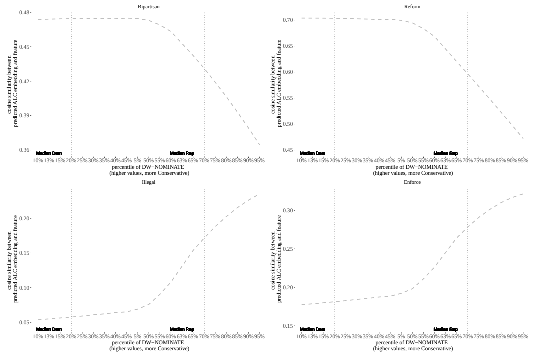
We then predict an ALC embedding for the target words at each percentile of the NOMINATE score and compute its cosine similarity with a small set of handpicked features. We strategically focus on words that are typically conservative or typically liberal in relation to the focal word to understand. We did this just for the tweets from never treated politicians for giving us a better sense of this measure and to define which words may be more conservative related than others which regard the specific target words.

In Figure 4.5.3 we present the evolution of cosine similarity for specific words as the NOMINATE score increases. From these plots, for example, we observe how the predicted ALC embedding for focal word *immigration* is closer to *illegal* and *enforce* at higher values of the NOMINATE score. On the other hand, it is closer to *bipartisan* and *reform* at lower values. Similar trends are observed for the other focal words, with words related to a conservative (liberal) slant becoming more (less) prominent as the NOMINATE score increases. We then identify the specific words used by Republicans and Democrats when talking about the four target words. These are words that are used particularly by just one of the two parties, while the other never used them or rarely used them. We show the 10 most used words for: immigration in Table 4.A.9;

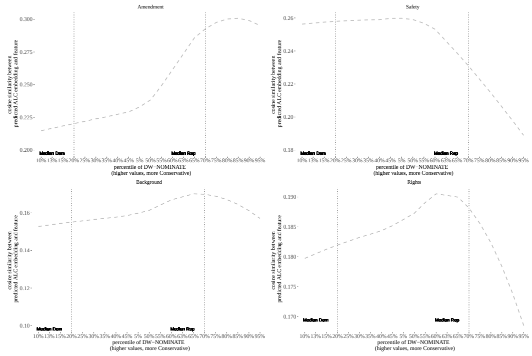
[11] This method is built on Khodak et al. (2018), which introduced ALC.

[12] It captures the liberal-conservative spectrum on economic matters

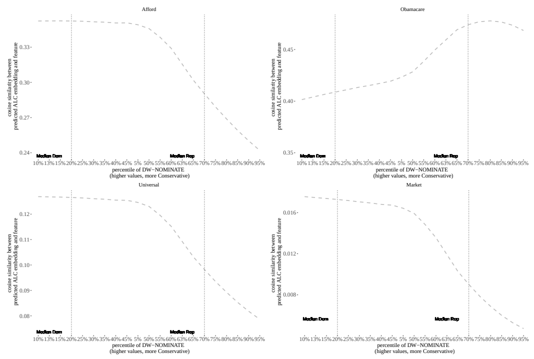
Figure 4.5.3: Slant - Never Treated



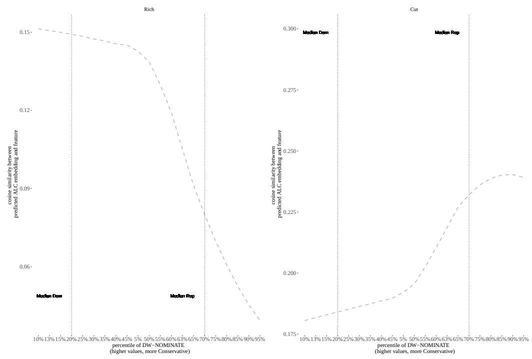
(a) *Immigration*



(b) *Guns*



(c) *Health Care*



(d) *Taxation*

Notes: These figures show the predicted ALC embedding for 4 different focal words: immigration, guns, health care and taxation. For each focal words we handpicked words related to the focal words but typically used by conservative or liberal politicians. We run this analysis for never treated politicians. We plot the cosine similarity between predicted ALC embedding and the focal word over the percentile of DW-NOMINATE (higher values, more Conservative). Higher values of cosine similarity means that the handpicked word is linked to the focal word more in the tweets of the more conservative Representative, while low values mean the opposite (the word is more used in talking about the focal word in tweets from more liberal politicians). We mark the median Democrat and median Republican.

gun in Table 4.A.10; health care in Table 4.A.11 and tax in Table 4.A.12.

After having showed how we proxy the conservative slant, we now focus our attention on the treated politicians. Particularly we split our main sample in two periods: pre-treatment (January-March 2013) and a post-treatment (January-March 2014). We compare cosine similarity of never treated politicians to treated politicians in the pre and post treatment period. To ensure comparability, both periods are chosen to be far from any potential primary or general elections (in 2014, the primary elections started in April, and the general elections were held in November). Our analysis involves Democrats and Republicans among the US Representatives, resulting in four observations for each party: never treated in the pre-period, never treated in the post-period, treated in the pre-period, and treated in the post-period. For each party and target word (i.e., immigration, guns, health care, taxation), we compute the cosine similarity and dot product scores of the handpicked words used in reference to the specific target word. By narrowing down our analysis to a sub-sample, we can concentrate solely on the features used in the tweets of this period. In particular, we can choose a smaller set of carefully selected words. We address this issue by utilizing the vector obtained from the pre-trained embedding of the specific handpicked word, rather than using the word itself.

To analyze the effect of treatment, we employ a 2x2 difference-in-differences-style approach, comparing treated and untreated units before and after the treatment. It is important to note that due to the nature of working with cosine similarity and dot product scores, we do not have standard errors in this case. As such, the results serve as suggestive evidence of an increase in the conservative slant, although we cannot establish a strong causal relationship. We present the results of this exercise in Table 4.A.13 for the target word immigration, Table 4.A.14 for the target word gun, Table 4.A.15 for the target word health care, and Table 4.A.16 for the target word taxation. These tables contain the cosine similarity and dot product scores assigned to each handpicked word with respect to the specific target word.

We then construct the 2x2 matrices for each party and we compute the difference in differences result comparing the dot product[13] of treated and not treated tweets before and after the treatment. We run this analysis specifically for the target word "immigration" as it exhibited the most distinct pattern along the conservative-liberal dimension. Upon examining the results, we observed evident trends in the handpicked words, indicating a shift towards either a more (less) conservative (liberal) stance. The findings are presented in four tables: Table 4.A.17, Table 4.A.18, Table 4.A.19, and Table 4.A.20, corresponding to the handpicked words “illegal", “enforce", “bipartisan", and “reform" respectively. From the tables, it is evident that the words “illegal" and “enforce" exhibit a clear conservative pattern, with increased importance after the treatment for both Republican and Democrat representatives. Conversely, the word "bipartisan" shows a decrease in importance for candidates of both parties when discussing immigration issues, revealing a decline in the liberal slant. As for the word "reform," typically used by liberal candidates when referring to immigration topics, its score decreases for Democrat representatives while increasing for Republicans, rendering the evidence for this word less apparent than the previous ones.

4.6 Conclusion

In this paper, we examine how a change in the traditional media content affects the online content as well. Specifically, we focus on the changes in local TV news content that occur following the acquisition of local TV stations by the broadcast group

[13] Rodriguez, Spirling and Stewart (2021) suggests in their paper that the dot product works better in these cases.

Sinclair.

In this essay, we begin by delving into the profound impact of Sinclair's acquisitions on both TV stations online content and politicians' discourse. Initially, we analyze the Twitter activity of TV stations and find that, after a Sinclair entry, they shift their attention from local politics to national issues. These findings corroborate existing literature, highlighting how Sinclair's influence extends to online content as well. This finding contributes the literature by showing that despite social media and traditional media have different characteristics and audiences, the content produced for traditional media can be also suitable for social media.

To assess the impact on politicians' online discourse, we conduct a comprehensive analysis of US Representatives' Twitter feeds. We develop a novel measure to gauge their focus on local issues by counting mentions of municipalities within their congressional districts. By applying a Bert topic model to these local tweets, we distinguish between tweets referring or sponsoring a local visit of the Representative and those discussing local events and policies. Additionally, we employ the innovative "A la carté" embedding regression technique to quantify the conservative slant in their communication.

Our findings reveal several key insights. Firstly, we observe a significant decrease in attention to local issues within the Twitter feeds of US Representatives following Sinclair's acquisitions. Notably, the number of mentions of municipalities experiences a 33% decline after Sinclair enters a media market. This effect becomes more pronounced over time, particularly in the first quarter after entry. Importantly, this change in behavior is not influenced by party affiliation, incumbency, or the political campaign period. This reduction is mainly seen in the US Representatives' tweets about local politics, indicating a potential shift in attention away from local political matters in their social media communications. However, tweets related to their personal local visits remain relatively unaffected. Furthermore, we find that this change in behavior does not impact the number of metrics a politician receives.

Moreover, we report some evidences demonstrating that after a Sinclair acquisition, treated politicians exhibit an increase in their conservative slant, confirming the conservative influence of the TV broadcast group. We focus on four politically relevant and divisive topics: immigration, guns, health care, and taxation. By comparing selected words to these target topics and assessing the cosine similarity and dot product scores, we observe clear patterns after a Sinclair entry. Words used more frequently by conservative politicians experience an increase in their similarity score for both Republicans and Democrats, while words more commonly used by liberal politicians become less important.

In overall, this research sheds light on the powerful impact of media content on politicians' behavior, emphasizing how Sinclair's acquisitions not only shape TV station content but also influence politicians' discourse and communication style, particularly in relation to local issues and conservative slant.

These findings are instrumental in enhancing our comprehension of the broader influence of media, extending beyond its impact on election outcomes and voter behavior as shown in previous studies (Gentzkow, Shapiro and Sinkinson, 2011; DellaVigna and Kaplan, 2007). Additionally, they shed light on how media influences the way politicians choose to communicate their messages. In conclusion, these results provide important insights into the mechanisms through which media content gets translated into the political realm and underscore the importance of understanding the impact of media on politics in the modern era.

Appendices

4.A Appendix A - Tables

Table 4.A.1: Descriptive Statistics

	Observations	Mean	SD	Min	Max
			TV Stations		
Local Politics topic	13,190	0.1320	0.0795	0.0005	0.5845
National Politics topic	13,190	0.1801	0.0937	0.0122	0.8789
Mentions US Representatives (Ihs)	13,190	1.8398	1.1102	0	3.5843
Treatment TV Stations	13,190	0.0877	0.2829	0	1
			US Representatives		
Place Mentions (Ihs, Wins 5%)	8,016	1.3623	1.1761	0	3.4667
Place Mentions (Ln + 0.1, Wins 5%)	8,016	0.1391	1.8356	-2.3025	2.7788
Place Mentions (Ln + 1, Wins 5%)	8,016	1.0713	0.9398	0	2.8332
Place Mentions (Wins 5%)	8,016	3.5684	4.5552	0	16
Place Mentions (Ihs, Wins 1%)	8,016	1.3772	1.2052	0	4.0256
Place Mentions (Ihs, Wins 10%)	8,016	1.3349	1.1309	0	3.0931
State Mentions in Congressional Speeches (Ihs, Wins 5%)	8,016	0.1965	0.5025	0	1.8184
Dummy Place Mentioned	8,016	0.6782	0.4672	0	1
Dummy Local Slant	8,016	0.7008	0.4579	0	1
Tweets about local place (Ihs)	8,016	1.3365	1.1727	0	4.8520
Tweets about local visit (Ihs)	8,016	0.3814	0.6682	0	3.9124
Tweets about local politics (Ihs)	8,016	1.2130	1.1163	0	4.6053
Dummy about local visit (Ihs)	8,016	0.2917	0.4546	0	1
Dummy about local politics (Ihs)	8,016	0.6506	0.4767	0	1
Nr Tweets US Representatives (Ihs)	8,016	4.1071	1.0499	1.8184	5.7494
Likes US Representatives (Share)	8,016	2.7270	15.1852	0	968.9818
Retweets US Representatives (Share)	8,016	47.9970	1768.928	0	141724.1
Replies US Representatives (Share)	8,016	2.1914	7.9214	0	349.3333
Treatment	8,016	0.4211	0.4938	0	1
Treatment continuous	8,016	0.2719	0.3880	0	1
Number of Places in each CD	8,016	64.2904	61.8499	1	420
Population district	8,016	708464.8	28532.08	524961	784020
Nr Tweets pre-treatment	8,016	134.8952	141.6234	1	1350

Notes:This table shows the descriptive statistics of our variables.

Table 4.A.2: Effect of Sinclair Entry on TV Stations' Twitter Metrics

	Ihs Tweets	Share Likes	Share Replies	Share Retweets
	(1)	(2)	(3)	(4)
	Panel A: TWFE			
Sinclair	-0.1007*	-0.1491***	-0.0315***	-1.6620
	(0.0576)	(0.0382)	(0.0062)	(2.0954)
	Panel B: BJS			
Sinclair	-0.0880	-0.1447***	-0.0326***	-2.2290
	(0.0643)	(0.0362)	(0.0071)	(1.6505)
Mean Dep. Variable	6.9964	0.3729	0.1388	8.8849
Observations	14,040	14,040	14,040	14,040
Clusters (DMAs)	195	195	195	195
Month FE	Yes	Yes	Yes	Yes
Station FE	Yes	Yes	Yes	Yes

Notes: This table shows estimates of Equation 4.1 which shows the effect of Sinclair's entry on the metrics (tweets, likes, retweets, replies) received by a TV station. Panel A shows estimates using the TWFE estimator, while Panel B reports the BJS estimator. The regressor of interest is an indicator variable equal to one after Sinclair acquires the TV station. We report the a specification including year-month and TV station fixed effects. Standard errors are clustered at the media market level. *p<0.1; **p<0.05; ***p<0.01

Table 4.A.3: Effect of Sinclair Entry on Politicians' Twitter Metrics

	Ihs Tweets	Share Likes	Share Replies	Share Retweets
	(1)	(2)	(3)	(4)
	Panel A: TWFE			
Sinclair	-0.0886	0.1484	2.5479	-9.8269
	(0.1241)	(0.6470)	(1.5517)	(21.2179)
	Panel B: BJS			
Sinclair	-0.0891	0.3089	-0.0570	-7.0350
	(0.0929)	(0.6150)	(0.6955)	(11.8106)
Mean Dep. Variable	4.1071	2.7270	2.1914	47.9970
Observations	7,992	7,992	7,992	7,992
Clusters (Representatives)	334	334	334	334
Month FE	Yes	Yes	Yes	Yes
MOC FE	Yes	Yes	Yes	Yes
State by Month FE	Yes	Yes	Yes	Yes
Population District x Year FE	Yes	Yes	Yes	Yes
Number of Places x Year FE	Yes	Yes	Yes	Yes

Notes: This table shows estimates of Equation 4.3 which shows the effect of Sinclair's entry on the metrics (tweets, likes, retweets, replies) received by a US Representative. Panel A shows estimates using the TWFE estimator, while Panel B reports the BJS estimator. The regressor of interest is an indicator variable equal to one after Sinclair enters the media market that covers the congressional district. We report the most complete specification including year-month and congressional district fixed effects, state by month fixed effects and controlling for population district and number of municipalities of the congressional district interacted with year fixed effects. Standard errors are clustered at the congressional district level. *p<0.1; **p<0.05; ***p<0.01

Table 4.A.4: Effect of Sinclair Entry on State Mentions in Politicians' Speeches

	Ihs Place Mentions				
	(1)	(2)	(3)	(4)	(5)
Sinclair	-0.0932	-0.1120*	-0.1550*	-0.1547*	-0.1572*
	(0.0602)	(0.0670)	(0.0867)	(0.0869)	(0.0894)
Mean Dep. Variable	0.6943	0.6943	0.6943	0.6943	0.6943
Observations	4,828	4,828	4,828	4,828	4,828
Clusters (Representatives)	334	334	334	334	334
Month FE	Yes	Yes	Yes	Yes	Yes
MOC FE	Yes	Yes	Yes	Yes	Yes
State Time Trends	No	Yes	No	No	No
State by Month FE	No	No	Yes	Yes	Yes
Population District x Year FE	No	No	No	Yes	Yes
Number Places in CD x Year FE	No	No	No	No	Yes

Notes: This table shows estimates of Equation 4.3 which shows the effect of Sinclair's entry on the number of times a state is mentioned in a representative's congressional speech. We apply an inverse hyperbolic transformation to the outcome variable and we winsorize it at 5%. The regressor of interest is an indicator variable equal to one after Sinclair enters the media market that covers the congressional district. Different columns report different specifications of Equation 4.3. Column 1 reports a specification with district and month by year fixed effects. In column 2 we add state specific linear time trends. In Column 3 we control for state by year-month fixed effects and in Column 4 we control for the population interacted by year fixed effects. In column 5 we add also the number of places present in a CD interacted with year fixed effects as control. We report estimates for every months the US Representative has talk in the House of Representatives. Standard errors are clustered at the congressional district level. *p<0.1; **p<0.05; ***p<0.01

Table 4.A.5: Effect of Sinclair Entry on Place Mentions in Politicians' Tweets - Robustness Table

	Place Mentions							
	Baseline	Dummy	Log	Log + 0.1	Log + 1	Wins 1%	Wins 10%	Poisson
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sinclair	-0.3322**	-0.1091**	-0.1825	-0.5127**	-0.2613**	-0.3317**	-0.3138**	-0.3876**
	(0.1464)	(0.0489)	(0.1276)	(0.2141)	(0.1190)	(0.1383)	(0.1512)	(0.1886)
	Panel B: BJS							
Sinclair	-0.2162*	-0.1422***	0.0579	-0.4436***	-0.1624*	-0.2202**	-0.2165*	
	(0.1107)	(0.0340)	(0.0919)	(0.1580)	(0.0897)	(0.1057)	(0.1130)	
Mean Dep. Variable	1.3623	0.6782	1.2567	0.1390	1.0713	1.3349	1.3772	3.5684
Observations	7,992	7,992	5,302	7,992	7,992	7,992	7,992	7,992
Clusters (Representatives)	334	334	334	334	334	334	334	334
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MOC FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State by Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Population District x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number Places in CD x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows estimates of Equation 4.3 which shows the effect of Sinclair's entry on different count models of the number of tweets about a local place in the US Representatives Twitter feed. Each column represent a different outcome variable. In column 1 we our baseline outcome variable (the ihs transformation of the number of tweets about a local place); in column 2 we use a dummy variable taking value 1 if in the month the US representative tweets about a local constituencies of her district ; in column 3 the log transformation of the number of mentions ; in column 4 the log +0.1 transformation of the number of mentions ; in column 5 the log + 1 transformation of the number of mentions; in column 6 the inverse hyperbolic sine transformation of the number of mentions winsorized at 1% and in column7 winsorized at 10% ; and finally in column 8 we present the Poisson estimator. We present the estimations of our most rigorous specification, which includes year-month, congressional district, state by month fixed effects, and the interaction of the number of places present in a CD and the population of the congressional by year fixed effects. Panel A presents the results using the TWFE estimators, while we use the Borusyak, Jaravel and Spiess (2021) estimator in panel B Standard errors are clustered at the congressional district level. *p<0.1; **p<0.05; ***p<0.01

Table 4.A.6: Effect of Sinclair Entry on Nr of Tweets about Local Places

	Dummy Tweets Local Places		
	All	No Visits	Visits
	(1)	(2)	(3
	Panel A: TWFE		
Sinclair	-0.1091**	-0.1082**	-0.0242
	(0.0488)	(0.0498)	(0.0548)
	Panel B: BJS		
Sinclair	-0.1422***	-0.1720***	0.0227
	(0.0339)	(0.0351)	(0.0431)
Mean Dep. Variable	0.6782	0.6507	0.2916
Observations	7,992	7,992	7,992
Clusters (Representatives)	334	334	334
Month FE	Yes	Yes	Yes
MOC FE	Yes	Yes	Yes
State by Month FE	Yes	Yes	Yes
Population District x Year FE	Yes	Yes	Yes
Number Places in CD x Year FE	Yes	Yes	Yes

Notes: This table shows estimates of Equation 4.3 which shows the effect of Sinclair's entry on the number of tweets about a local place in the US Representatives Twitter feed. Each column represent a different outcome variable. In column we have the a dummy identifying a month with at least one tweet about a local place. In column 2 we have a dummy identifying a month with at least one tweet about a local place not identified by a local visit; while in column we have a dummy identifying a month with at least one tweet about a local place identified with a visit. We apply an inverse hyperbolic transformation to the outcome variable and we winsorize it at 5%. Panel A shows TWFE estimates, while Panel B shows Borusyak et al. (2021) estimates. The regressor of interest is an indicator variable equal to one after Sinclair enters the media market that covers the congressional district. We report the most rigourous specification including district and month by year fixed effects and state by year-month fixed effects. We also control for the population interacted by year fixed effects and the number of places present in a CD interacted with year fixed effects as control. Standard errors are clustered at the congressional district level. *p<0.1; **p<0.05; ***p<0.01

Table 4.A.7: Effect of Sinclair Entry on Tweets about Local Places - Heterogeneity by Political Campaigning

	Local Visit TWFE (1)	No Local Visit TWFE (2)	Local Visit BJS (3)	No Local Visi BJS (4)
1.Sinclair	-0.0076	-0.3221**	0.0191	-0.2535***
	(0.1011)	(0.1413)	(0.0598)	(0.0909)
1.Sinclair#1.Political_Campaign	-0.0133	0.1333	0.0554	-0.0515
	(0.0702)	(0.1012)	(0.1153)	(0.1625)
Mean Dep. Variable	0.3814	1.2130	0.3814	1.2130
Observations	7,992	7,992	7,992	7,992
Clusters (Representatives)	334	334	334	334
Month FE	Yes	Yes	Yes	Yes
MOC FE	Yes	Yes	Yes	Yes
State by Month FE	Yes	Yes	Yes	Yes
Population District x Year FE	Yes	Yes	Yes	Yes
Number Places in CD x Year FE	Yes	Yes	Yes	Yes

Notes: This table shows estimates of the interaction of our treatment with a dummy identifying the political campaigning period (August-November 2014) on the number of times a US Representative tweets about a local place. We divide between local visits about a local visit and not about a local visit (local politics). We report the most rigourous specification including district and month by year fixed effects and state by year-month fixed effects. We also control for the population interacted by year fixed effects and the number of places present in a CD interacted with year fixed effects as control. Standard errors are clustered at the congressional district level. *p<0.1; **p<0.05; ***p<0.01

Table 4.A.8: Effect of Sinclair Acquisition on US Representatives Mentions in TV stations' Tweets

	Ihs Count US Representative Mentioned - Surname and Rep words					
	TWFE (1)	TWFE (2)	Poisson (3)	Poisson (4)	BJS (5)	BJS (6)
Sinclair	-0.0898	-0.1056	-0.1092*	-0.1252*	-0.0822	-0.1045
	(0.0648)	(0.0704)	(0.0598)	(0.0640)	(0.0701)	(0.0830)
Mean Dep. Variable	1.8398	1.8398	1.8398	1.8398	1.8398	1.8398
Observations	13,190	13,190	13,190	13,190	13,190	13,190
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
TV Station FE	Yes	Yes	Yes	Yes	Yes	Yes
DMA x month FE	No	Yes	No	Yes	No	Yes

Notes: This table shows estimates of Equation 4.1 for the inverse hyperbolic sine transformation of number of mentions a US Representative receive from a TV station Twitter activity in a given month. The regressor of interest is a dummy variable taking value 1 when a TV station is acquired by Sinclair. We reports a specification with year-month fixed effects and station fixed effects; and we then add also dma by year-month fixed effects. Different columns report different estimators: columns 1 and 2 the TWFE; columns 3 and 4 the Poisson transformation and columns 5 and 6 the Borusyak, Jaravel and Spiess (2021). Standard errors are clustered at the media market level. *p<0.1; **p<0.05; ***p<0.01

Table 4.A.9: Specific words used by Republicans and Democrats associated to the focal word: immigration

Never Treated	
Dem	Rep
modernization	undocumented
comprehensive	illegal
priorities	deporting
blueprint	combatting
integration	laws
strengthening	enforcing
bill	feds
bipartisanship	expedited
accountability	us-mexico
piecemeal	approves

Notes: This table shows the 10 specific and with the highest cosine similarity words used by never treated republican and democrat candidates associated to the focal word: immigration.

Table 4.A.10: Specific words used by Republicans and Democrats associated to the focal word: gun

Never Treated	
Dem	Rep
violence	proposals
prevention	nra
bloodshed	amend
crime	priorities
redouble	agenda
hate	limiting
deter	feds
enforcement	policies
offenders	amendment
senseless	controls

Notes: This table shows the 10 specific and with the highest cosine similarity words used by never treated republican and democrat candidates associated to the focal word: gun.

Table 4.A.11: Specific words used by Republicans and Democrats associated to the focal word: health care

Never Treated	
Dem	Rep
needy	overhaul
ensuring	reform
subsidized	legislation
unaffordable	enact
accessing	repeal
providers	pension
improving	subsidy
choices	bills
skyrocketing	jeopardize
benefiting	taxes

Notes: This table shows the 10 specific and with the highest cosine similarity words used by never treated republican and democrat candidates associated to the focal word: health care.

Table 4.A.12: Specific words used by Republicans and Democrats associated to the focal word: taxes

Never Treated	
Dem	Rep
benefits	enact
paying	overhaul
giveaways	simplifying
expense	reforming
refunds	repeal
eliminating	obamacare
deduction	burdensome
breaks	stricter
incentives	unfunded
reductions	protections

Notes: This table shows the 10 specific and with the highest cosine similarity words used by never treated republican and democrat candidates associated to the focal word: taxes.

Table 4.A.13: Slant for the target word immigration

group	cosine	dot product	period	feature	target
D-0	0.02	0.18	pre	illegal	immigration
D-0	0.04	0.42	post	illegal	immigration
D-1	0.00	0.09	pre	illegal	immigration
D-1	0.05	0.56	post	illegal	immigration
R-0	0.08	0.84	pre	illegal	immigration
R-0	0.12	1.17	post	illegal	immigration
R-1	0.08	0.98	pre	illegal	immigration
R-1	0.12	1.45	post	illegal	immigration
D-0	0.06	0.54	pre	enforce	immigration
D-0	0.08	0.77	post	enforce	immigration
D-1	0.05	0.51	pre	enforce	immigration
D-1	0.10	0.91	post	enforce	immigration
R-0	0.05	0.46	pre	enforce	immigration
R-0	0.08	0.73	post	enforce	immigration
R-1	0.04	0.44	pre	enforce	immigration
R-1	0.13	1.14	post	enforce	immigration
D-0	0.23	1.98	pre	reform	immigration
D-0	0.26	2.26	post	reform	immigration
D-1	0.24	2.09	pre	reform	immigration
D-1	0.24	2.16	post	reform	immigration
R-0	0.17	1.63	pre	reform	immigration
R-0	0.18	1.61	post	reform	immigration
R-1	0.16	1.33	pre	reform	immigration
R-1	0.25	2.24	post	reform	immigration
D-0	0.23	1.98	pre	reform	immigration
D-0	0.26	2.26	post	reform	immigration
D-1	0.24	2.09	pre	reform	immigration
D-1	0.24	2.16	post	reform	immigration
R-0	0.17	1.63	pre	reform	immigration
R-0	0.18	1.61	post	reform	immigration
R-1	0.16	1.33	pre	reform	immigration
R-1	0.25	2.24	post	reform	immigration

Notes: This table shows the cosine similarity and the dot product scores of the handpicked words with respect the target word immigration. We present for each party and word four valued: for the never treated in the pre period, for the never treated in the post period, and for the treated units in the pre and post period.

Table 4.A.14: Slant for the target word gun

group	mean_cosine	mean_dot_product	period	feature	target
D-0	0.06	0.59	pre	rights	gun
D-0	0.09	0.95	post	rights	gun
D-1	0.07	0.65	pre	rights	gun
D-1	0.06	0.60	post	rights	gun
R-0	0.08	0.85	pre	rights	gun
R-0	0.13	1.26	post	rights	gun
R-1	0.09	0.92	pre	rights	gun
R-1	0.27	3.21	post	rights	gun
D-0	0.06	0.50	pre	safety	gun
D-0	0.06	0.47	post	safety	gun
D-1	0.05	0.45	pre	safety	gun
D-1	-0.02	-0.19	post	safety	gun
R-0	0.10	0.91	pre	safety	gun
R-0	-0.06	-0.59	post	safety	gun
R-1	0.10	1.08	pre	safety	gun
R-1	0.01	0.09	post	safety	gun
D-0	0.09	0.78	pre	background	gun
D-0	0.06	0.50	post	background	gun
D-1	0.01	0.11	pre	background	gun
D-1	0.00	-0.01	post	background	gun
R-0	0.01	0.05	pre	background	gun
R-0	-0.03	-0.29	post	background	gun
R-1	-0.01	-0.13	pre	background	gun
R-1	-0.03	-0.32	post	background	gun
D-0	0.11	1.05	pre	amendment	gun
D-0	0.11	1.12	post	amendment	gun
D-1	0.11	1.06	pre	amendment	gun
D-1	-0.01	-0.10	post	amendment	gun
R-0	0.14	1.44	pre	amendment	gun
R-0	0.05	0.45	post	amendment	gun
R-1	0.14	1.37	pre	amendment	gun
R-1	0.29	3.44	post	amendment	gun

Notes: This table shows the cosine similarity and the dot product scores of the handpicked words with respect the target word gun. We present for each party and word four valued: for the never treated in the pre period, for the never treated in the post period, and for the treated units in the pre and post period.

Table 4.A.15: Slant for the target word health care

group	cosine	dot product	period	feature	target
D-0	0.16	1.60	pre	affordable	health care
D-0	0.12	1.14	post	affordable	health care
D-1	0.13	1.07	pre	affordable	health care
D-1	0.08	0.80	post	affordable	health care
R-0	0.16	1.44	pre	affordable	health care
R-0	0.11	1.05	post	affordable	health care
R-1	0.11	1.10	pre	affordable	health care
R-1	0.10	0.89	post	affordable	health care
D-0	0.06	0.62	pre	universal	health care
D-0	0.04	0.40	post	universal	health care
D-1	0.04	0.37	pre	universal	health care
D-1	0.02	0.15	post	universal	health care
R-0	0.05	0.41	pre	universal	health care
R-0	0.03	0.29	post	universal	health care
R-1	0.02	0.21	pre	universal	health care
R-1	0.02	0.17	post	universal	health care
D-0	0.01	0.10	pre	market	health care
D-0	-0.01	-0.09	post	market	health care
D-1	-0.03	-0.30	pre	market	health care
D-1	0.01	0.14	post	market	health care
R-0	0.01	0.12	pre	market	health care
R-0	0.00	0.04	post	market	health care
R-1	0.02	0.25	pre	market	health care
R-1	0.03	0.25	post	market	health care
D-0	0.17	1.60	pre	obamacare	health care
D-0	0.13	1.24	post	obamacare	health care
D-1	0.14	1.18	pre	obamacare	health care
D-1	0.10	0.90	post	obamacare	health care
R-0	0.15	1.33	pre	obamacare	health care
R-0	0.17	1.65	post	obamacare	health care
R-1	0.13	1.24	pre	obamacare	health care
R-1	0.12	1.03	post	obamacare	health care

Notes: This table shows the cosine similarity and the dot product scores of the handpicked words with respect the target word health care. We present for each party and word four valued: for the never treated in the pre period, for the never treated in the post period, and for the treated units in the pre and post period.

Table 4.A.16: Slant for the target word taxation

group	cosine	dot product	period	feature	target
D-0	0.04	0.41	pre	rich	tax
D-0	0.01	0.10	post	rich	tax
D-1	0.04	0.34	pre	rich	tax
D-1	0.02	0.16	post	rich	tax
R-0	-0.01	-0.13	pre	rich	tax
R-0	-0.01	-0.05	post	rich	tax
R-1	-0.001	-0.04	pre	rich	tax
R-1	-0.01	-0.08	post	rich	tax
D-0	0.11	0.91	pre	cut	tax
D-0	0.05	0.43	post	cut	tax
D-1	0.12	1.00	pre	cut	tax
D-1	0.04	0.34	post	cut	tax
R-0	0.09	0.74	pre	cut	tax
R-0	0.05	0.47	post	cut	tax
R-1	0.10	0.82	pre	cut	tax
R-1	0.05	0.39	post	cut	tax

Notes: This table shows the cosine similarity and the dot product scores of the handpicked words with respect the target word taxation. We present for each party and word four valued: for the never treated in the pre period, for the never treated in the post period, and for the treated units in the pre and post period.

Table 4.A.17: 2x2 matrix for the handpicked word Illegal

	Pre	Post	Difference (Post-Pre)	Party	Feature
Treated	0.09	0.56	0.47	Dem	Illegal
Never	0.18	0.42	0.24	Dem	Illegal
Difference (Never-Treated)	0.09	-0.14	**0.23**	Dem	Illegal
Treated	0.98	1.45	0.47	Rep	Illegal
Never	0.84	1.17	0.33	Rep	Illegal
Difference (Never-Treated)	-0.14	-0.28	**0.14**	Rep	Illegal

Notes: This table shows the 2x2 difference-in-differences matrix for understanding how evolve the dot product of the handpicked word illegal with respect the target word immigration. We present the post-pre difference, the never treated-treated difference and the overall difference (DiD style) for both parties.

Table 4.A.18: 2x2 matrix for the handpicked word Enforce

	Pre	Post	Difference (Post-Pre)	Party	Feature
Treated	0.51	0.91	0.4	Dem	Enforce
Never	0.54	0.77	0.23	Dem	Enforce
Difference (Never-Treated)	0.03	-0.14	**0.17**	Dem	Enforce
Treated	0.44	1.14	0.7	Rep	Enforce
Never	0.46	0.73	0.27	Rep	Enforce
Difference (Never-Treated)	0.02	-0.41	**0.43**	Rep	Enforce

Notes: This table shows the 2x2 difference-in-differences matrix for understanding how evolve the dot product of the handpicked word enforce with respect the target word immigration. We present the post-pre difference, the never treated-treated difference and the overall difference (DiD style) for both parties.

Table 4.A.19: 2x2 matrix for the handpicked word Bipartisan

	Pre	Post	Difference (Post-Pre)	Party	Feature
Treated	2.2	2.17	-0.03	Dem	Bipartisan
Never	2.13	2.57	0.44	Dem	Bipartisan
Difference (Never-Treated)	-0.07	0.4	**-0.47**	Dem	Bipartisan
Treated	1.08	0.73	-0.35	Rep	Bipartisan
Never	1.83	1.51	-0.32	Rep	Bipartisan
Difference (Never-Treated)	0.75	0.78	**-0.03**	Rep	Bipartisan

Notes: This table shows the 2x2 difference-in-differences matrix for understanding how evolve the dot product of the handpicked word bipartisan with respect the target word immigration. We present the post-pre difference, the never treated-treated difference and the overall difference (DiD style) for both parties.

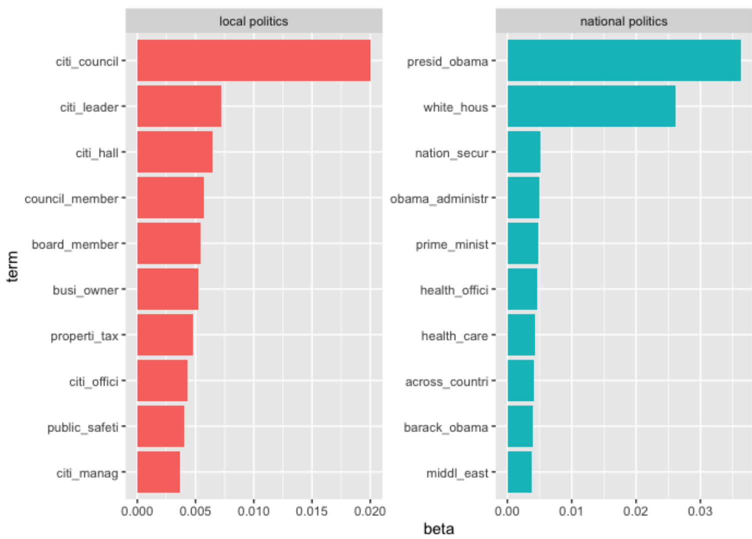
Table 4.A.20: 2x2 matrix for the handpicked word Reform

	Pre	Post	Difference (Post-Pre)	Party	Feature
Treated	2.09	2.16	0.07	Dem	Reform
Never	1.98	2.26	0.28	Dem	Reform
Difference (Never-Treated)	-0.11	0.1	**-0.21**	Dem	Reform
Treated	1.33	2.24	0.91	Rep	Reform
Never	1.63	1.61	-0.02	Rep	Reform
Difference (Never-Treated)	0.3	-0.63	**0.93**	Rep	Reform

Notes: This table shows the 2x2 difference-in-differences matrix for understanding how evolve the dot product of the handpicked word reform with respect the target word immigration. We present the post-pre difference, the never treated-treated difference and the overall difference (DiD style) for both parties.

4.B Appendix B - Figures

Figure 4.B.1: LDA Topic Model - National and Local politics

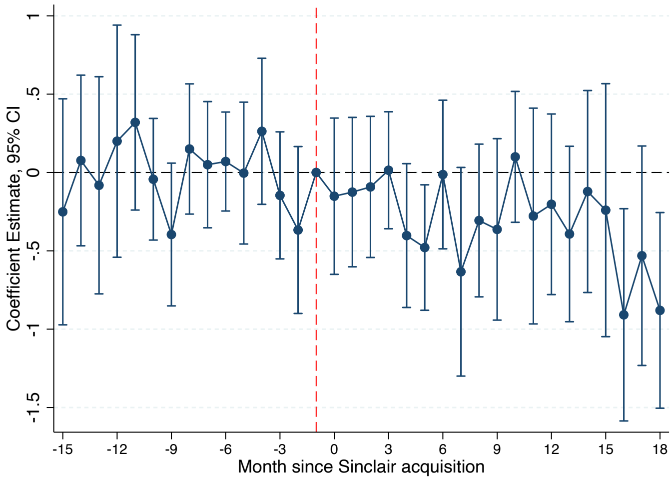


Notes: This figure shows the 10 most used bigrams of the local and national topics identified by the LDA topic model on the TV stations corpus.

Figure 4.B.2: Bert Topic Model - Local Tweets

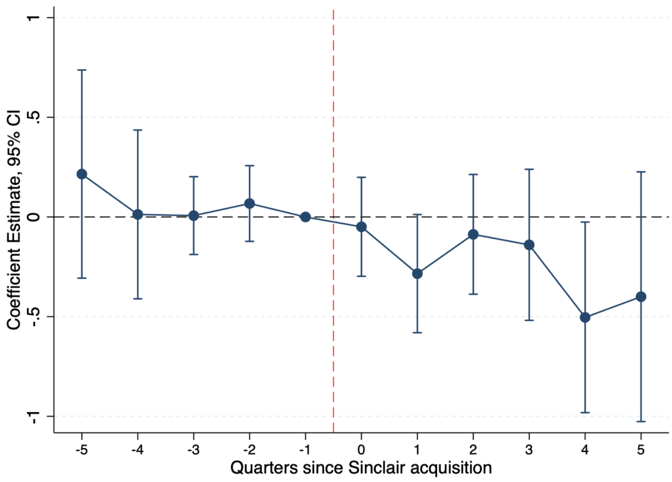
Notes: This figure shows the 20 topics most discussed in US Representatives tweets about local places. We identify Topic 0 (and -1) as topic about a local visits. The others are topic about local episodes, local politics or local policies.

Figure 4.B.3: Effect of Sinclair Entry on Place Mentions in Politicians' Tweets, Event Study (TWFE)



Notes: This graph shows the TWFE dynamic treatment effect estimates of the effect of Sinclair acquisition on our main outcome variable: the inverse hyperbolic sine transformation of the count of local places by month on congresspeople tweets. The dashed red vertical lines indicate the timing of the acquisition. The dashed red horizontal line shows 95% confidence intervals for standard errors clustered at the congressional district level.

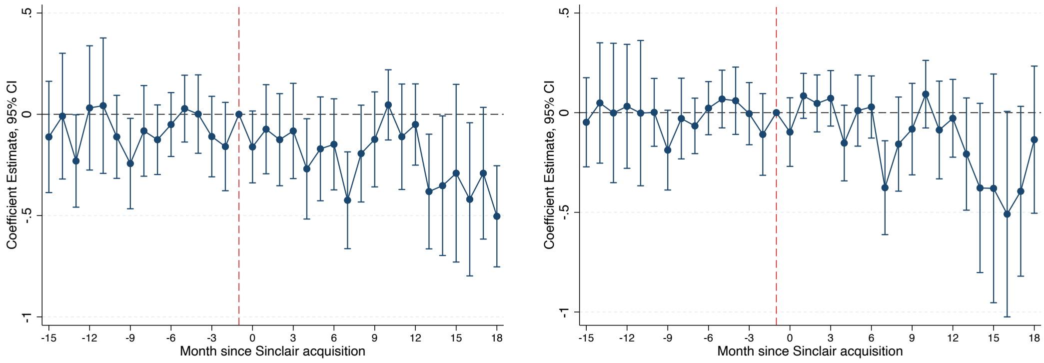
Figure 4.B.4: Effect of Sinclair Entry on Place Mentions in Politicians' Tweets, Event Study Quarter (TWFE)



(a) *Ihs Place Mentioned*

Notes: This graph shows the TWFE dynamic treatment effect estimates of the effect of Sinclair acquisition on our main outcome variable: the inverse hyperbolic sine transformation of the count of local places by month on congresspeople tweets. In this case the dataset is not at the month level, but at the quarter of the year level. The dashed black horizontal line shows 95% confidence intervals for standard errors clustered at the congressional district level.

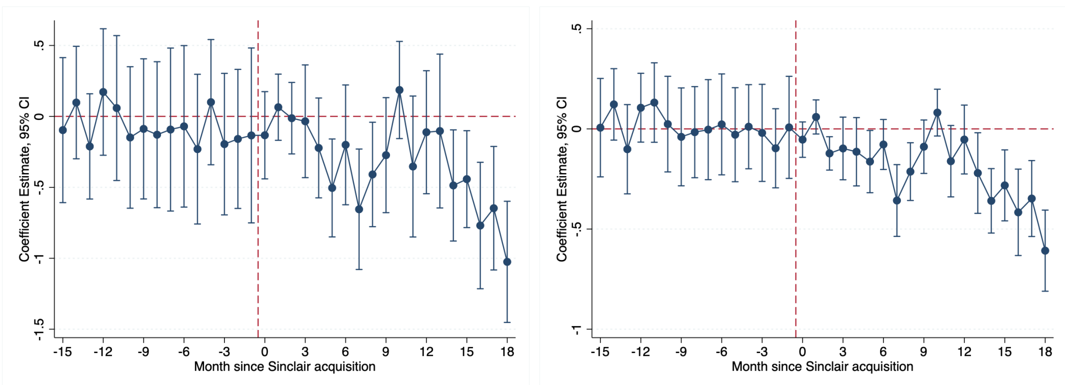
Figure 4.B.5: Effect of Sinclair Entry on Place Mentions in Politicians' Tweets, Event Study (TWFE)



(a) *Dummy Place Mentioned* **(b)** *Dummy Local Slant*

Notes: This graph shows the TWFE dynamic treatment effect estimates of the effect of Sinclair acquisition on a dummy taking value one if in a given month a congressperson tweeted at least once about a local place (Panel (a)) and using a local bigram (Panel (b)). The dashed red vertical lines indicate the timing of the acquisition. The dashed red horizontal line shows 95% confidence intervals for standard errors clustered at the congressional district level.

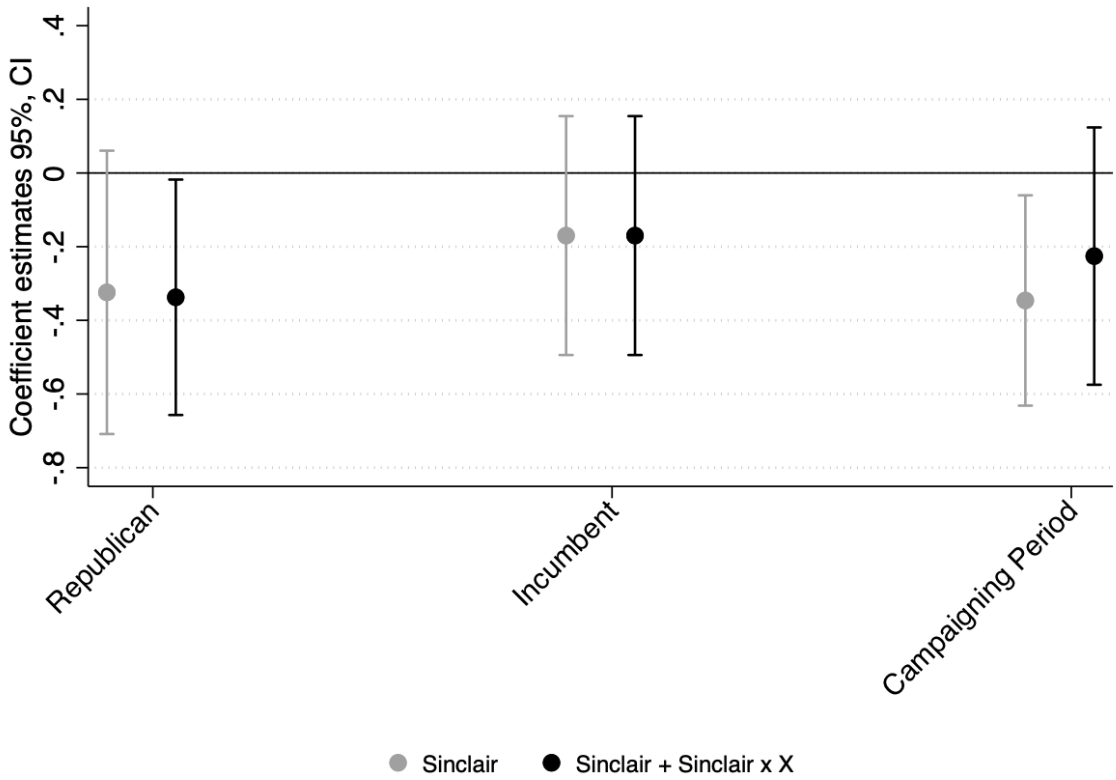
Figure 4.B.6: Effect of Sinclair Entry on Probability To Tweet about Local Politics, Event Study (BJS)



(a) *Ihs Nr Tweets Local Places - NO Visits* **(b)** *Dummy Tweets Local Places - NO Visits*

Notes: This graph shows dynamic treatment effect estimates of the effect of Sinclair acquisition on the ihs transformation of the number of tweets about local politics (Panel (a)) and a dummy taking value one if in a given month a congressperson tweeted at least once about local politics (Panel (b)). The dashed red vertical lines indicate the timing of the acquisition. The dashed red horizontal line shows 95% confidence intervals for standard errors clustered at the congressional district level. The plots are constructed using the machinery suggested by Borusyak, Jaravel and Spiess (2021).

Figure 4.B.7: Heterogeneity



Notes: This graph shows heterogeneity for our results. We run three different type of heterogeneity: by party, by incumbent, by political campaigning. In the first, we interact our outcome variable with a dummy taking value 1 if the US Representative is a member of the Republican party; in the second one we interact the treatment variable with a dummy taking value 1 if the US Representative was present also in the previous Congress cycle; and in the third one we interact it with a dummy value taking value 1 for the last 5 months of a congressional period (during the political campaigning)

Chapter 5

General conclusion

This dissertation has explored the intricate relationship between political economy, political communication, and some of its implications. Through three essays, the research has shed light on how political discourse reacts to real world shocks and how this might have influences on policy-making, democratic processes, law enforcement behavior, and social media. The findings of these essays have significant implications for both scholars and policymakers.

So far, the literature in this topic showed that political communication, while essential for democratic societies, can have both positive and negative consequences. It can facilitate transparency, accountability, and public participation, but it can also contribute to misinformation, manipulation, echo chambers, and toxic behavior. The power of language in politics cannot be understated, as it shapes public opinion and political outcomes.

In this dissertation, I have demonstrated that the way politics is communicated is not just shaped by outside events, but it also plays a big role in spreading the effects of these events. In Chapter 2, I reported how this back-and-forth relationship shows that real-world events affect political communication, and in turn, political communication can amplify the effects of those events. This teaches us that we need to understand how the real world and political communication affect each other. I have shown this in an essay that explores the contagious nature of political polarization and its implications for the democratic process and the composition of Congress. By employing a comprehensive measure of polarization and analyzing short-term dynamics, this research provides insights into how polarization can spread across different political issues, leading to increased gridlock and reduced legislative productivity. These findings underscore the urgent need for strategies that promote bipartisan collaboration and bridge the divide between ideological factions. By fostering constructive dialogue and finding common ground, policymakers can work towards effective governance and the advancement of public interests.

Furthermore, in the dissertation I have shown how language extends its reach into law enforcement behavior, shaping arrests practices, and perpetuating also discrimination. This is indeed the object of Chapter 3 of this dissertation, where I investigated the influence of presidential rhetoric on law enforcement officers' behavior, specifically examining the consequences of the "War on Drugs" campaign during the Reagan administration. The research uncovers a disturbing pattern of systemic discrimination, as heightened law enforcement activities disproportionately target minority communities. These findings highlight the pressing need for criminal justice reforms that address racial biases, promote fairness, and ensure equal treatment under the law. Policymakers and law enforcement agencies must work together to enact policies that foster trust, promote community engagement, and reduce the disparate impact of law enforcement activities on marginalized populations.

Finally, the strategic manipulation of political communication does not stop there; it also extends to social media platforms, as I showed in Chapter 4 of this dissertation. Indeed, this essay delves into the impact of changes in traditional media content on social media communication, focusing on the acquisition of local TV stations by Sinclair. The research reveals a shift in discourse and ideology among U.S. Representatives following Sinclair's entry into media markets. This raises concerns about the potential polarization and ideological homogenization within the House of Representatives, which may hinder constructive debate and compromise. These findings emphasize the importance of media diversity, independent journalism, and critical media literacy. Policymakers and citizens alike must prioritize a vibrant and pluralistic media landscape to ensure a well-informed electorate and robust democratic deliberation.

By employing rigorous econometric frameworks and innovative text analysis techniques, this dissertation advances the understanding of the dynamics between political language and its outcomes. The case study of the United States provides valuable insights into the complexities of political communication within a specific context, given its global influence, diverse economic systems, rich data, and policy relevance.

Given these findings, this dissertation provides valuable insights for policymakers and scholars. It underscores the need for responsible and inclusive political communication that fosters understanding, promotes social cohesion, and addresses systemic biases. To navigate the challenges of the modern political landscape, policymakers must prioritize evidence-based policy-making, engage in transparent and respectful dialogue, and strive for policies that promote justice, equality, and the common good. The implications of this research extend beyond academia, serving as a call to action for policymakers, civil society organizations, and citizens alike. By understanding the complex dynamics between political discourse and various societal spheres, we can collectively work towards creating a more inclusive, equitable, and democratic society.

This thesis is for me the first step into the research in economics. With this work I wanted to link some of the new machine learning developments into the political economy field. There is a large and increasing literature doing this, and I hope to have contributed, at least in a minimum part, to this revolution. Nowadays, It is becoming always more important to interact different disciplines and techniques together to understand the complexity of the world we have around.

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